Essays in Total Factor Productivity Measurement

D I S S E R T A T I O N

zur Erlangung des akademischen Grades

Dr. rer. pol.
im Fach Volkswirtschaftslehre

eingereicht an der
Wirtschaftswissenschaftlichen Fakultät
Humboldt-Universität zu Berlin

von
Herrn Battista Severgnini, M. Sc. Econ.
geboren am 01.04.1977 in Crema (Italien)

Präsident der Humboldt-Universität zu Berlin:
Prof. Dr. Dr. h.c. Christoph Markschies

Dekan der Wirtschaftswissenschaftlichen Fakultät:
Prof. Oliver Günther, Ph.D.

Gutachter:
1. Prof. Michael C. Burda, Ph.D.
2. Prof. Irwin L. Collier, Ph.D.

eingereicht am: 10. November 2009
Tag der mündlichen Prüfung: 08. Februar 2010


JITTER

Ai miei genitori

Abstract

This dissertation consists of theoretical and empirical contributions to the study on Total Factor Productivity (TFP) measurement. The first chapter surveys the literature on the most used techniques in measuring TFP and surveys the limits of these frameworks. I give special attention to the growth accounting procedure, the Solow residual and the dual approach analyzing the impact of measurement errors and spillover effects. Moreover, I consider an alternative measurement based on the Malmquist index. Finally, I review the most used parametric techniques found in the literature for estimating the technological change and externalities in the production function, based on standard parametric methods and State-space models. The second chapter considers data generated from a Real Business Cycle model and studies the quantitative extent of measurement error for the Solow residual as a measure of TFP growth when the capital stock is measured with error and when capacity utilization and depreciation are endogenous. Furthermore, it proposes two alternative measurements of TFP growth which do not require capital stocks: the first one, the Direct Substitution (DS) method, is appropriate when the economy under analysis is far from its steady-state. The second one, the General Difference (GD) method, relies on the economy‘s proximity to a steady-state path. The two methods show root mean squared error in realizations of the artificial economy which are as low as one-third of that of the Solow residual. Furthermore, TFP growth estimates are computed and compared using data from the new and old German federal states. The third chapter proposes a new methodology based on State-space models in a Bayesian framework. Applying the Kalman Filter to artificial data, it proposes a computation of the initial condition for productivity growth based on the properties of the Malmquist index. Comparing these results using the Gibbs-sampler, I find that the RMSE of this procedure can be also two-thirds lower than for the Solow Residual when capital contains measurement error. In addition, the procedure is extended to panel data. The empirical application employs Danish industry data. The fourth chapter introduces a new approach for identifying possible spillovers emanating from new technologies on productivity combining a counterfactual decomposition derived from the main properties of the Malmquist index and the econometric technique introduced by Machado and Mata (2005). Moreover, I consider a new definition of technological space based on firms' propensity to invest in communication and in innovative processes. Applying this methodology to a dataset of Italian manufacturing firms and employing a definition of technological space based on network activities, I find that externalities are relevant for TFP growth and the most productive firms are also the main recipients of ICT spillovers.
Keywords: Total factor productivity, Solow residual, measurement error, Malmquist index, Kalman Filter, Gibbs sampler, ICT spillover, technological space, network effects, Machado and Mata technique.

Zusammenfassung

Diese Dissertation umfasst sowohl einen theoretisches als auch einen empirischen Beitrag zur Analyse der Messung der gesamten Faktorproduktivität (TFP). Das erste Kapitel inspiziert die bestehende Literatur über die häufigsten Techniken der TFP Messung und gibt einen Überblick über deren Limitierung. Besonderes Augenmerk lege ich dabei auf die Wachstumszerlegung, das Solow Residuum und den dualen Ansatz zur Analyse des Einflusses von Messfehlern und Spill-over Effekten. Darüber hinaus berücksichtige eine alternative Messgröße, die auf dem Malmquist Index basiert. Schlussendlich, gebe ich einen überblick über die parametrischen Methoden, die am meisten in der Literatur verwendet werden, um technischen Fortschritt und die Externalitäten der Produktionsfunktion zu schätzen, die wiederrum auf standardmäßigen parametrischen Methoden und Zustands-Raum-Modellen beruhen. Das zweite Kapitel betrachtet Daten, die durch ein Real Business Cycle Modell generiert wurden und untersucht das quantifizierbare Ausmaßvon Messfehlern des Solow Residuums als ein Maßfür TFP Wachstum, wenn der Kapitalstock fehlerhaft gemessen wird und wenn Kapazitätsauslastung und Abschreibungen endogen sind. Desweiteren werden zwei alternative Maße des TFP Wachstums vorgeschlagen, die Angaben über den Kapitalstock nicht erfordern: das erste, die Methode Direkter Substitution (DS), ist geeignet, wenn die analysierte Volkswirtschaft weit von ihrem gleichmäßigen Wachstumspfad entfernt ist. Das zweite Maß, die Allgemeine Differenzen Methode (GD - General Difference method) beruht auf der Annahme, dass sich die Volkswirtschaft nah am gleichmäßigen Wachstumspfad befindet. Diese beiden Methoden weisen mittlere quadratische Fehler in den Realisationen der künstlichen Volkswirtschaft auf, die kleiner als ein Drittel derer des Solow Residuums sind. Außerdem wird das TFP Wachstum geschätzt und mit den Daten für die alten und neuen Bundesländer verglichen. Das dritte Kapitel schlägt eine neue Methodologie in einem bayesianischen Zusammenhang vor, die auf Zustands-Raum-Modellen basiert. Der Kalman Filter wird auf artifizielle Daten angewendet und so wird ein Ansatz zur Berechnung der Anfangsbedingung des Produktivitätswachstums gezeigt, der auf den Eigenschaften des Malmquist Indexes basiert. Bei einem Vergleich dieser Ergebnisse mit Hilfe des Gibbs-Samplers finde ich, dass auch diese Methode zu zwei-drittel niedrigeren mittleren quadratischen Fehlern verglichen mit dem Solow Residuum führt, wenn Kapital nur fehlerhaft gemessen werden kann. Diese Vorgehensweise wird außerdem auf Panel Daten erweitert. Die empirische Anwendung konzentriert sich auf Dänische Industriedaten. Das vierte Kapitel führt einen neuen Ansatz zur Bestimmung möglicher Spill-over Effekte auf Grund neuer Technologien auf die Produktivität ein und kombiniert eine kontrafaktische Zerlegung, die von den Hauptannahmen des Malquist Indexes abgeleitet wird mit ökonometrischen Methoden, die auf Machado and Mata (2005) zurückgehen. Desweiteren nehme ich eine neue Definition des technologischen Raums an, die auf den Neigungen von Firmen in sowohl kommunikative als auch innovative Prozesse zu investieren beruht. Wenn diese Methode auf Daten italienischer Firmen des verarbeitenden Gewerbes angewandt wird und wenn die Definition des technologischen Raums auf Netzwerkaktivitäten beruht, so finde ich, dass Externalitäten relevant für das TFP Wachstum sind und dass die produktivsten Firmen diejenigen sind, die auch zu einem früheren Zeitpunkt von ICT Spill-over-Effekten profitiert haben.

Schlagwörter: Gesamte Faktorproduktivität, Solow Residuum, Messfehler, Malmquist Index, Gibbs Sampler, ICT-Spill-over-Effekte, technologischer Raum, Netzwerkeffekte, Machado und Mata Methode.

Acknowledgments

During my doctoral studies I have received a lot of comments, support and encouragement from several people which I am very happy to acknowledge. First of all, I would like to thank Michael C. Burda for his invaluable advice and the lively discussions and for co-authoring the second chapter of this thesis. I am also indebted to my second supervisor, Irwin L. Collier, for very precious suggestions. Moreover, I wish to thank all the faculty of the *Berlin Doctoral Program in Economics & Management Science* for stimulating and rigorous classes.

This dissertation has also benefited from feedbacks and discussion with, in alphabetical order, Jaap Bos, Drew Creal, Annalisa Croce, Carl-Johan Dalgaard, Herman van Dijk, Stefano Fachin, Andrea Gavosto, John Hassler, Mun Ho, Dale Jorgenson, Martin Junge, Kristiaan Kerstens, Per Krusell, Lisbeth La Cour, Marco Leonardi, Bartosz Maćkowiak, Emi Nakamura, Cheti Nicoletti, Sergio Perelman, Morten Ravn, Günther Rehme, José-Victor Ríos-Rull, Albrecht Ritschl, Esben Anton Schultz, Robin Sickles, Anders Sørensen, Sarah Spiekermann, Christian Stoltenberg, Mathias Trabandt, Harald Uhlig, Mark Vancautteren, Giovanni Luca Violante, Mark Weder and Mirko Wiederholt.

In addition, I have obtained important suggestions from seminar and conference participants at Humboldt University Berlin, Copenhagen Business School, the Milano Labour Lunch Seminar at Bocconi University, at the IV North American Productivity Workshop in New York, the 2^{nd} Nordic Summer Symposium in Macroeconomics in Sandbjerg, at the Workshop on Growth, ICT, and Human Capital in Copenhagen, at the 11^{th} and the 12^{th} European Workshop on Efficiency and Productivity Analysis in Lille and Pisa, at the International Conference on Measurement Error in Birmingham, at the 8^{th} IWH-CIREQ Macroeconometric Workshop in Halle-Salle and at the 24^{th} Annual Congress of the European Economic Association in Barcelona.

Furthermore, this research was financially supported by the InterVal (01AK702A) project , which is funded by the German Ministry of Education and Research and by the specific Targeted Research Project "EUKLEMS−2003. Productivity in the European Union: A Comparative Industry Approach", supported by the European Commission within the Sixth Framework Programme with Contract No. 502049 (SCS8). I am also extremely grateful to the Innocenzo Gasparini Institute for Economic Research at Bocconi University in Milan and to the Center for Economic and Business Research in Copenhagen for their generous hospitality during research stays where parts of this dissertation have been written. I thank Peter Møllegaard and Anders Sørensen for giving me the opportunity to finish this thesis at Copenhagen Business School.

I owe a very special thank to Tito Boeri for his great support and encouragement during my stays at Fondazione Rodolfo Debenedetti in Milan.

I am also very grateful to my former colleagues at Humboldt University in Berlin, in particular, Sebastian Braun, Dorothee Schneider, Runli Xie and Fang Yao, with whom I was pleased to work. Daniel Neuhoff provided excellent and unflagging research assistance for the second chapter of this dissertation.

Attilio Luigi Pasetto and *Uni Credit Group* are acknowledged for kindly providing the data considered in the fourth chapter. A particular thank to William Baumol for allowing me to use a computer painting (the *Jitter*) from his wonderful and colorful art gallery.

Last but not least, I am extremely thankful to Lars Börner and Juliane Scheffel not only for their academic advice during my stay in Berlin, but especially for their great friendship.

Contents

Technical change is like God.
It is much discussed,
worshipped by some,
rejected by others,
but little understood.

(Ross Thomson in
Mokyr (1992))

Productivity isn´t everything,
but in the long run
is everything

(Krugman (1990))

List of Figures

List of Tables

1. TFP Measurements: An Overview

1.1. Introduction

Technology is considered the major cause of economic growth. Social scientists agree on the role of ideas and innovations in acting as a *deus ex machina* in somehow increasing total factor productivity (TFP) (Mokyr (2005)), which in turn raises world income per capita (Maddison (2005)), transforms the production processes and modifies the way to run a business. Several compelling examples of the solid link between new technologies and growth can be found in the history: since the 18^{th} century, with the Industrial Revolution, the introduction of new General Purpose Technologies (GPTs), such as steam engines, electricity, automobiles and telephones, has exponentially increased the standard of living. Furthermore, in the second half of the 1990s, for some countries, for example, the US, the investment in new Information and Communication Technologies (ICT) implied a radical changes in the underlying structure of its economy, which experienced, after an extended and unexpected stagnation during the 70s and the 80s, high levels of output growth associated with a strong, across-the-board productivity boom.

Measuring TFP growth is a key element not only for quantifying the impact of new technologies but also for understanding why an economic unit is richer than another one or whether the advances in technological goods can fragment the production processes and have stark and different effects on the employment composition, with large positive shifts in demand of skilled workers. In economics, management and operations research, it is possible to choose from several sets of parametric and non-parametric procedures for estimating technological change. In detail, Diewert (1981) divided these techniques into different groups: growth accounting procedures, mostly based on index, estimations of cost function, estimation of production function, and nonparametric methods, also known in the literature as data envelopment analysis (DEA). In most of these frameworks, technological growth is derived as a difference between the output produced and the inputs used. Even if these procedures are in general quite simple and straightforward to implement, accurate measurement of TFP growth represents one of the most challenging task in macroeconomics for several reasons. First of all, while output and employment are directly measurable in the production process, capital is not observable and should be constructed considering a number of assumptions regarding investment, the depreciation rate and capacity utilization. In addition, increasing returns to scale or spillovers can bias upward the TFP growth results. Finally, once all the inputs are correctly measured, technological progress can be influenced by other factors, such as culture, institutions, climate conditions and initial endowments.

This thesis is structured in four chapters and consists of theoretical and empirical contributions to the study and measurement of TFP growth. It is especially devoted to the strengths and the weaknesses of the productivity estimation exploring the quantitative extent of capital measurement error and the possible spillover effects emanated by the investment in ICT for the Solow Residual (Solow (1957)) and econometric frameworks. In addition, this thesis proposes different new methodologies for estimating TFP growth, most of them exploiting the properties derived from DEA procedures, especially the Malmquist index. Finally, after illustrating these techniques, I consider three different applications using, respectively, macro, industry and firm-level data.

Chapter 1 surveys the literature on the most commonly used techniques in measuring TFP and oversees the limits of these frameworks. In the first part, I focus on the growth accounting procedure, the Solow residual and the dual approach to analyze the impact of measurement errors and spillover effects. Moreover, I analyze the notion of TFP growth in the context of current literature, focusing on endogenous and biased technological change and the modification of the growth accounting framework when technological change is embodied in capital. Next, I review the most frequently used parametric techniques found in the literature for estimating the technological change and externalities in the production function, based on standard parametric methods and State-space models. Finally, I consider an alternative measurement based on DEA, concentrating on the Malmquist index.

Chapter 2 is coauthored with Michael C. Burda. Considering data generated by a Real Business Cycle model, it studies the quantitative extent of measurement error for the Solow residual as a measure of TFP growth when the capital stock is measured with error and when capacity utilization and depreciation are endogenous. Furthermore, it proposes two alternative measurements of TFP growth which do not require capital stocks: the first one, the Direct Substitution (DS) method, is appropriate when the economy under analysis is far from its steady-state. The second one, the General Difference (GD) method, relies on the economy's proximity to a steady-state path. The two methods show root mean squared error in realizations of the artificial economy which are as low as one-third of that of the Solow residual. Furthermore, we compute and compare TFP growth estimates using data from the new and old German federal states.

Chapter 3 proposes a new methodology based on State-space models in a Bayesian framework. This econometric procedure provides highly accurate results with the advantage that capital series, which are often affected by measurement errors, are unnecessary. Moreover, applying the Kalman Filter to artificial data, I propose a computation for the initial condition of TFP growth based on the properties of the Malmquist index. Comparing the results using the Gibbs-sampler, I find that the root mean squared error of this procedure can be two-thirds lower than the Solow residual when it is computed following the standard growth accounting procedure. In addition, I extend this framework to panel data. The empirical application focuses on Danish industry data. The comparison between the TFP growth measures provided by the Danish national statistics and the Kalman filter estimations suggest that capital can play an important role in estimating technological change, especially in industries where it is more difficult to obtain a precise measure of the inputs.

Chapter 4 proposes a new approach for identifying spillovers that emanate from new technologies on productivity combining a counterfactual decomposition derived from the main Malmquist index properties and modifying the econometric technique introduced by Machado and Mata (2005). A new definition of technological space based on firms' propensity to invest both in communication and in innovative processes is also considered. Applying this methodology to a dataset of Italian manufacturing firms, I find that externalities are relevant for TFP growth once the definition of technological space is based on network activities and that the most productive firms are also the foremost recipients of ICT spillovers.

The remainder of this chapter is organized as follows. Section 2 is devoted to the study of the Solow residual and the dual approach. Section 3 considers the limitations of the growth accounting framework, especially when inputs are mismeasured and when capital utilization and spillover effects can overstate the value of the Solow residual. Moreover, it illustrates the concept of biased technological change and the modification of the growth accounting when technology is embodied in capital. Section 4 reviews the most used econometric frameworks for estimating TFP exploiting a translog production function and analyzes the special case of the parametric estimation of the Cobb-Douglas production function and the techniques considered for estimating spillover effects. Section 5 introduces the data envelopment analysis (DEA), devoting particular attention to the Malmquist index. Finally, Section 6 concludes.

1.2. The Growth Accounting Framework and the Solow Residual

Growth accounting is one of the most popular tools for analyzing the relevant source of growth and explaining the differences in productivity among different sectors or geographical regions. Introduced by the seminal contributions of Tinbergen (1942), Solow (1957), Kendrick (1961) and Denison (1962), and analyzed in details by Jorgenson and Griliches (1967), Barro (1999), Jorgenson (2005) and Hulten (2009), this framework has the goal of decomposing the observed economic growth into different factor inputs and a residual. The latter, also known in the literature as the Solow residual, is thought to capture TFP growth and other unexplained factors.

More precisely, the growth accounting framework considers a standard neoclassical production function

$$Y_t = F\left(A_t, K_t, N_t\right) \tag{1.1}$$

where K_t denotes capital available at the beginning of period t, and Y_t and N_t represent output and employment during period t,[1] while A_t represents the state of TFP. Solow approximated TFP growth as $\frac{\dot{Y}_t}{Y_t} - \alpha_t \frac{\dot{K}_t}{K_t} - (1 - \alpha_t) \frac{\dot{N}_t}{N_t}$, i.e., the difference of the observable growth rate of output and a weighted average of the growth of the two inputs, where α_t and $1 - \alpha_t$ are local output elasticities of capital and labor; a dot denotes the time derivative (e.g. $\dot{A} = dA/dt$). In practice, if the production function has a Hicks-neutral

[1] Jorgenson and Griliches (1967) suggest an extended framework where capital and labor can be decomposed into different quality classes.

form, i.e., $Y_t = A_t F(K_t, N_t)$, the Solow decomposition is generally implemented in discrete time, as (see Barro (1999) and Barro and Sala-I-Martin (2005)):

$$\frac{\Delta A_t}{A_{t-1}} = \frac{\Delta Y_t}{Y_{t-1}} - \alpha \frac{\Delta K_t}{K_{t-1}} - (1-\alpha)\frac{\Delta N_t}{N_{t-1}} \tag{1.2}$$

In competitive factor markets, output elasticities of capital and labor equal aggregate factor income shares, which are constant in the case of the Cobb-Douglas production function,[2] i.e.,

$$Y_t = A_t K_t^{\alpha} N_t^{1-\alpha}, \tag{1.3}$$

for other technologies that allow for factor substitution, equation (1.2) gives a reasonable first-order approximation. A central reason for the Solow residual's enduring popularity as a measure of TFP growth is its robustness; it measures the contribution of observable factor inputs to output growth solely on the basis of theoretical assumptions (constant returns to scale, perfect competition in factor markets) and external information (factor income shares), without recourse to statistical techniques (Griliches (1996)).

Yet the Solow residual itself is hardly free of measurement error.[3] Jorgenson and Griliches (1967, 1972) argue that the Solow residual is only a "measure of our ignorance" and necessarily contaminated by measurement error and model misspecification. In contrast, Denison (1972) and others extend the TFP measurement paradigm to a larger set of production factors, and confirmed that the unexplained residual is the most important factor explaining output growth. Ever since Christensen et al. (1973) raised concerns about the choice of weights α and $1-\alpha$, it has become commonplace to employ the so-called Törnqvist index specification of the Solow residual, presented here as a logarithmic approximation:

$$\Delta \ln A_t = \Delta \ln Y_t - \bar{\alpha}_{t-1} \Delta \ln K_t - (1 - \bar{\alpha}_{t-1}) \Delta \ln N_t \tag{1.4}$$

where $\bar{\alpha}_{t-1} = \frac{\alpha_{t-1}+\alpha_t}{2}$ (see Törnqvist (1936)). This formulation reduces measurement error and is exact if the production function is translog (Diewert (1976)). Denison (1962) and Hall and Jones (1999) employ the Solow approximation across space as opposed to time to assess the state of technical progress relative to a benchmark economy.

1.2.1. The Dual Approach

An alternative way for computing TFP growth exploiting the growth accounting framework is represented by the dual approach. Relying on factor prices rather than the physical stocks of input, Jorgenson and Griliches (1967) and, more recently, Hsieh (2002) recompute the Solow residual considering the growth rates of factor prices, wage (ω) and capital rental price (κ), instead of the input quantities, thus the production function

[2] In Section 1.3, the assumption of constant factor shares is relaxed considering different types of production functions, for example, CES and translog.

[3] Solow himself wrote:

> *"[L]et me be explicit that I would not try to justify what follow by calling on fancy theorems on aggregation and index numbers. Either this kind of aggregate economics appeals or it doesn't.[...] If it does, one can draw some useful conclusions from the results."* Solow (1957: 312).

(1.1) can be rewritten as a cost function:

$$Y_t = \kappa_t K_t + \omega_t N_t, \tag{1.5}$$

which, differentiated with respect to time and after some rearrangements, gives

$$\frac{\Delta Y_t}{Y_{t-1}} = \alpha \left(\frac{\Delta \kappa_t}{\kappa_{t-1}} + \frac{\Delta K_t}{K_{t-1}} \right) + (1-\alpha) \left(\frac{\Delta \omega_t}{\omega_{t-1}} + \frac{\Delta N_t}{N_{t-1}} \right). \tag{1.6}$$

Combining (1.2) with (1.6) and under the assumption of constant returns to scale and perfect competition, TFP growth is given by

$$\frac{\Delta Y_t}{Y_{t-1}} - \alpha \frac{\Delta K_t}{K_{t-1}} - (1-\alpha) \frac{\Delta N_t}{N_{t-1}} = \frac{\Delta A_t}{A_{t-1}} = \alpha \left(\frac{\Delta \kappa_t}{\kappa_{t-1}} \right) + (1-\alpha) \frac{\Delta \omega_t}{\omega_{t-1}}. \tag{1.7}$$

In (1.7), the primal framework of growth accounting (left-hand side) is equal to the dual approach (right-hand side), where the rising price for a given factor can be sustained only if output is increasing.

A priori, if the production is assumed to exhibit constant returns to scale and perfect competition,[4] there is no theoretical reason for preferring one of the methodologies over the other. However, measurement errors in stocks should suggest the use of the dual approach. On the other hand, similar to Denison (1962), Hall and Jones (1999) and Aiyar and Dalgaard (2005) consider a cross-sectional approach of (1.6) and compare two sets of TFP estimates computed for a group of 22 OECD countries, finding discrepancies in the techniques because of data inconsistencies both in the user costs and physical costs of capital.

1.3. The Limits of Growth Accounting

Growth accounting and the definition of TFP growth itself are still topics of central importance in the current research agenda, and the study of a correct measurement of TFP change is relevant not only for empirical studies but also in theoretical models. One of the most striking examples is represented over the past 25 years by the real business cycle (RBC) models, where technological shocks drive almost all of these frameworks.[5] Several criticisms of the growth accounting approach represented by (1.2) have been raised in the literature, mostly in the last 15 years, because this classical framework is not able to explain different economic facts such as the complementarity between capital and skills and the causality between the massive investment in new types of capital such as ICT in most developed countries and their higher TFP growth. Even though not all of these problems are analyzed in the following chapters, it is worth having an overview of them. This section analyzes several limits of the growth accounting approach: 1) the capital measurement problem, 2) the concept of capital utilization, 3) the presence of spillover, 4) the possibility of production functions other than the Cobb-Douglas and the

[4] Roeger (1995) finds different TFP growth measurements in the US manufacturing using the two approaches and explains these differences with the presence of variable returns to scale, imperfect competition, and factor hoarding.

[5] The importance of TFP growth in RBC models is described in several articles. See, for example, King and Rebelo (1999), Kydland and Prescott (1993), Prescott (1986a) and Prescott (2006).

concept of biased technological change, and 5) the modification of the growth accounting when technological change is embodied in capital.

1.3.1. The Capital Measurement Problem

The capital stock poses a particular problem in growth accounting because it is not measured or observed directly, but rather constructed by statistical agencies using time series of investment expenditures. Measurement error is likely to be important for a number of reasons in addition to the initial condition problem for the capital stock. While output and employment are directly observable and readily quantifiable, capital must be estimated in a way which involves a number of controversial assumptions. In this context it is worth recalling the famous capital controversy between Cambridge University, led by Joan Robinson, and the Massachusetts Institute of Technology and in particular, Paul Samuelson (see Robinson (1953)).

In particular, the perpetual inventory method (PIM) simply integrates forward the "Goldsmith equation" (Goldsmith (1995))

$$K_{t+1} = (1 - \delta_t)\, K_t + I_t, \qquad t = 0, 1, \ldots \tag{1.8}$$

from some initial condition K_0, given sequences of investment expenditures $\{I_t\}$ and depreciation rates $\{\delta_t\}$. Formally, (1.8) can be solved from period 0 to period $t+1$ to yield

$$K_{t+1} = \left[\prod_{i=0}^{t} (1 - \delta_{t-i})\right] K_0 + \sum_{j=0}^{t} \left[\prod_{i=0}^{t} (1 - \delta_{t-i})\right] I_{t-j} \tag{1.9}$$

The current capital stock is the weighted sum of an initial capital value, K_0, and subsequent investment expenditures, with weights corresponding to their undepreciated components. If the depreciation rate is constant and equal to δ, (1.9) collapses to

$$K_{t+1} = (1 - \delta)^{t+1} K_0 + \sum_{j=0}^{t} (1 - \delta)^j I_{t-j}. \tag{1.10}$$

which is identical to Hulten (1990).

From the perspective of measurement theory, four general problems arise from using capital stock data estimated by statistical agencies.[6] First, the construction of capital stocks presumes an accurate measurement of the initial condition K_0. The shorter the series under consideration, the more likely such measurement error regarding the capital stock will affect the construction of the Solow residual. Second, it is difficult to distinguish truly utilized capital at any point in time from that which is idle. Solow (1957) also anticipated this issue, arguing that the appropriate measurement should be of *"capital in use, not capital in place"*. Third, depreciation is also fundamentally unobservable. For some sectors and some types of capital, it is difficult if not impossible to apply an appropriate depreciation rate; this is especially true of the retail sector.

[6] See Diewert and Nakamura (2007) for more a detailed discussion.

Fourth, many intangible input stocks such as cumulated research and development effort and advertising goodwill are not included in measured capital.

The Goldsmith equation (1.8) implies that mismeasurement of the initial capital stock casts a long shadow on the construction of the Solow residual. The problem can only be solved by pushing the initial condition sufficiently far back into the past; yet with the exception of a few countries,[7] sufficiently long time series for investment are unavailable. The perpetual inventory approach to constructing capital series was thus criticized by Ward (1976) and Mayes and Young (1994), who proposed alternative approaches grounded in estimation methods.[8]

Figure 1.1 contains two graphs that illustrate this point. On the left side, I display capital stock time series constructed using investment series generated from the stochastic growth model based on quarterly data and described in Chapter 2 (Section 3) with different initial values of K_0. To illustrate the impact of the initial capital value on productivity, estimate of the capital stock is inserted into (1.4) to calculate a Törnqvist index version of the Solow residual. Measurement error in K_0 will bias TFP growth computations when 1) depreciation δ is low and 2) the time series under consideration is short ($t-j$ is low). On the right side, I show the TFPG, expressed by $\ln\left(\frac{A_t}{A_{t-1}}\right)$, considering different values of K_0 and, similarly to the capital series represented in Figure 1.1, also TFPG has biased results dependent on the initial K_0: it takes more than 30 quarters to reach the convergence within 10%.

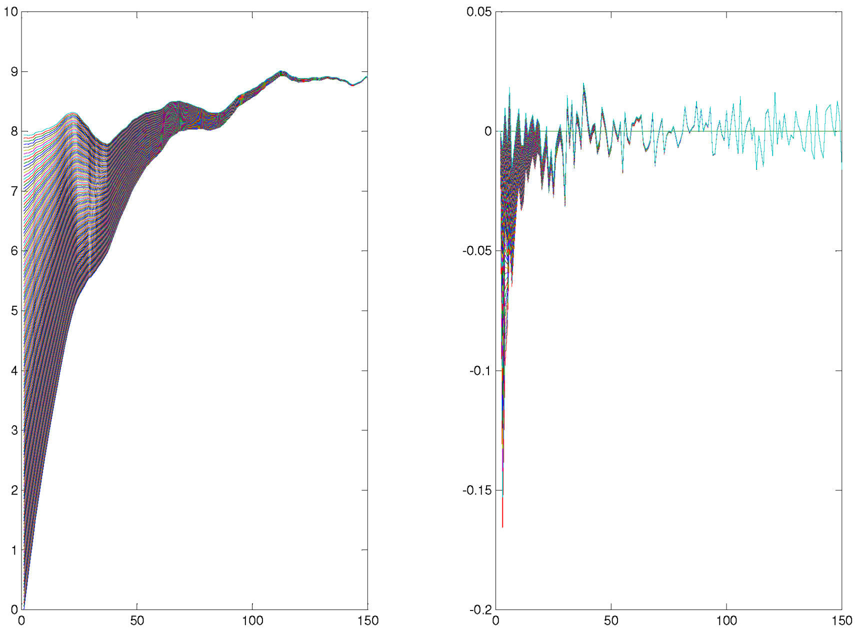
Several proposals for the initial value of capital can be found in the literature. Jacob et al. (1997) estimate the initial capital stock with artificial investment series for the previous century assuming that the investment grows at the average same rate of output. The US Bureau of Economic Analysis (BEA) assumes that investment in the initial period I_0, represents the steady state in which expenditures grow at rate g and are depreciated at rate δ, so a natural estimate of K_0 is given by $I_0\left(\frac{1+g}{\delta+g}\right)$.[9] Griliches (1980) proposes an initial condition $K_0 = \rho\frac{I_0}{Y_0}$ for measuring R&D capital stocks, where ρ is a parameter to be estimated. Over long enough time horizons and under conditions of stable depreciation, the initial condition problem should become negligible. Caselli (2005) assesses the quantitative importance of the capital measurement problem by the role played by the surviving portion of the initial estimated capital stock at time t as a fraction of the total, assuming a constant depreciation rate. He finds that measurement error induced by the initial guess is most severe for the poorest countries. To deal with this problem, he proposes two different approaches: for the richest countries the initial capital is approximated by a steady-state condition $K_0 = \frac{I_0}{(g+\delta)}$ where g is the investment growth rate; for the poorest countries, he applies a "lateral Solow decomposition",

[7]For example, Denmark and the US Statistical Office have respectively data on investment from 1832 and 1947; most industrialized economies only report data since the 1960s.

[8]In practice the OECD (2001) suggests comparing initial capital estimates with five different benchmarks: 1) *population census* take into account different types of dwellings from the Census; 2) *fire insurance records*; 3) *company accounts*; 4) *administrative property records*, which provides residential and commercial buildings at values at current market prices; and 5) *company share valuation*. Yet in the end, extensive data of this kind are unavailable, so such benchmarks are used to check the plausibility of estimates constructed from investment time series.

[9]See, for example, Reinsdorf and Cover (2005) and Sliker (2007).

Figure 1.1.: The consequences of different initial capital value and their impact on the Solow residual.



following Denison (1962) and Hall and Jones (1999) to the US economy corrected for the human capital, and estimates the capital stock as

$$K_0 = K_{US} \left(\frac{Y_0}{Y_{US}} \right)^{\frac{1}{\alpha}} \left(\frac{N_{US}}{N_0} \right)^{\frac{1-\alpha}{\alpha}} \tag{1.11}$$

where the index US refers to data to the first observation for the American economy in 1950. Caselli's innovative approach will lose precision if the benchmark economy is far from its steady state. In particular, the key assumption in (1.11) that TFP levels are identical to those in the US in the base year appears problematic, and are inconsistent with the findings of Hall and Jones (1999). Most important, there is little reason to believe that K_{US} was free of measurement error in 1950.

1.3.2. Capital Utilization and the Solow Residual

Even if capital utilization, i.e., the ratio of the actual level of capital effectively used from a sustainable maximum, is considered one of the leading indicator at the macroeconomic level (Christiano (1981)), most of the time, it is not taken into account in productivity measurement because of lack of data.

In the growth accounting framework, the production function (1.1) is extended by a capacity utilization component $U_t \in (0,1)$:

$$Y_t = F\left(A_t, U_t K_t, N_t\right), \tag{1.12}$$

and the Solow decomposition then becomes

$$\frac{\Delta A_t}{A_{t-1}} = \frac{\Delta Y_t}{Y_{t-1}} - \alpha\left(\frac{\Delta K_t}{K_{t-1}} + \frac{\Delta U_t}{U_{t-1}}\right) - (1-\alpha)\frac{\Delta N_t}{N_{t-1}} \tag{1.13}$$

In this case, the original Solow decomposition will overestimate (underestimate) the TFP measurement in case of an increase (decrease) of capacity utilization. The quantification of this change in the use of capital on TFP has been at the center of the debate. Even if Hall (1988) and Caballero and Lyons (1992) support the hypothesis that capacity utilization does not play any role in growth accounting because the service of capital flows at a constant rate, i.e. $\frac{\Delta U_t}{U_{t-1}} = 0$, new data confirm the thesis that utilization of capital should be taken into consideration because their fluctuations are volatile over time and tend to be confused with the Solow residual (Abbott et al. (1989), Gordon (1992), Basu (1996) and De Borger and Kerstens (2000)).

1.3.3. Spillover Effects and the Solow Residuals

In the literature on macroeconomics, several models consider economic growth based on increasing returns or spillovers (e.g., Romer (1986) and Lucas (1988)). A framework that describes the effects of externalities on the Solow residual can be found in Barro (1999), who considers (1.1) for firm i and represents it with a Cobb-Douglas production function as follows:

$$Y_i = AK_i^{\alpha} K^{\beta} N_i^{1-\alpha} \tag{1.14}$$

with $0 < \alpha < 1$, $\beta \geq 0$, N_i, and K_i being the firm's private inputs, while K is an indicator (for example, the sum or the average) of the level of knowledge in the economy and can be interpreted as knowledge-creating activities (e.g., research and development (R&D) (Griliches (1979)) or new technologies), physical components (Romer (1986)) or education (Lucas (1988)). If $\beta > 0$, a spillover effect is present: ideas useful for the production process can freely circulate across firms. Assuming that each firm has the same capital-labor ratio $k_i = k \equiv K/N$ at equilibrium, (1.14) can be rewritten as

$$Y_i = Ak_i^{\alpha} k^{\beta} N_i N^{\beta} \tag{1.15}$$

which can be aggregated into

$$Y = Ak^{\alpha+\beta} N^{1+\beta} = AK^{\alpha+\beta} N^{1-\alpha} \tag{1.16}$$

such that the Solow residual (1.2) can be rewritten for aggregate data as follows:

$$\frac{\Delta A_t}{A_{t-1}} = \frac{\Delta Y_t}{Y_{t-1}} - (\alpha+\beta)\frac{\Delta K_t}{K_{t-1}} - (1-\alpha)\frac{\Delta N_t}{N_{t-1}} \tag{1.17}$$

While the labor input is weighted correctly, the share for capital is understated by $\beta \geq 0$. Because this value is not directly observable,[10] the usual standard Solow residual calculation includes not only the rate of exogenous technological change but also the growth effect from spillover and increasing returns. $\beta \frac{\Delta K_t}{K_{t-1}}$.

1.3.4. TFP and non-Cobb-Douglas Production Technologies

Usually, the growth accounting decompositions assume constant-factor distributions of income at each point in time, which are usually obtained assuming a Cobb-Douglas production function and competitive factor pricing. Even if this assumption is derived by one of the generalized stylized facts introduced by Kaldor (1961) and exploited in a large number of RBC models,[11] it contains several drawbacks. First of all, empirical evidence provided by Blanchard (1997) shows that capital shares in business sectors in Continental Europe steadily increased in contrast with the stability observed during the period 1970-2005 in the US, Canada and UK. On the other hand, Bernard and Jones (1996), analyzing industry and country level data for 14 OECD countries, observe that labor shares vary substantially across countries and industries (especially in manufacturing and service); moreover, more recent data from NIPA and BLS shows that in the US, the factor shares of income are also quite volatile (Rìos-Rull and Santaeulália-Llopis (2009)). Blanchard (1997) attempts to explain the changes in the distribution of income deviation of marginal product in two different ways: 1) similar to Bruno and Sachs (1985), there could be a shift of the division of rents from workers to the owner of the firms if wages are determined by Nash bargaining, or 2) biased technological change.

The latter concept, introduced by Kennedy (1964) and Samuelson (1965), states that where inputs of the production function are not equally abundant, technological innovation affects not only TFP growth but also the composition of the inputs. The basic assumption of the theory of production is that a two-way relationship exists between the technology and the production function; i.e., all changes in technology affect the production functions, and all changes in the production function reflect the changes in technology. Technological changes may involve both a shift of the isoquants and a change in their slope. On one hand, if technological change is neutral, the effect is represented by only a parallel shift of the map of isoquants towards the origin; on the other hand, if technological change is also biased, the isoquants are affected by changes in both position and slope.

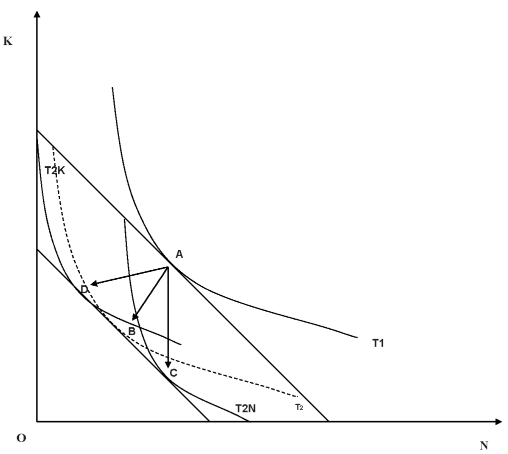
Figure 1.2 disentangles the direct and the biased technological changes representing the isoquants of production, using as inputs capital K and labor N given a certain technology T. Assuming that the economy at time $T1$ is on the equilibrium point A, the effect of a neutral technological change at time $T2$ shifts the isoquant towards the origin in a parallel way such that the new equilibrium point is B. On the other hand, the introduction of a biased technological change also contributes to a change in the slope of the isoquant, where the new equilibrium point is represented by C or

[10] This value can be estimated, even if some simultaneity problems could arise.

[11] Some models considering nonconstant share can be found in Gomme and Greenwood (1995), Hansen and Prescott (2005) and Choi and Rìos-Rull (2008).

D, depending on the structure of relative prices: point C displays the case of labor-augmenting technological change in contexts characterized by relatively low wage levels (technology $T2N$), while point D represents the case of a capital-intensive technical change in contexts characterized by relatively high wage levels (technology $T2K$).

Figure 1.2.: Direct and Biased Technological Change



If the economy is not well represented by a Cobb-Douglas production function, the assumption of constant shares could seriously bias the computation of TFP growth. Even if Solow (1957) itself identifies the productivity level A_t of (1.2) as *any kind of shift in the production function*, the Solow residual can be considered as just a proxy of the direct technological change. In addition, if the factors are not equally abundant, the effects of biased technological innovations are not accounted by the standard growth accounting approach. In the literature, several contributions recognize these problems related to the traditional growth accounting framework and propose several alternative generalizations of the Cobb-Douglas production function. Among them, one option can be individuated in the constant elasticity of substitution (CES) between labor and capital production function, introduced by Arrow et al. (1961) and developed by Kendrick and Sato (1963):

$$Y_t = A_t F\left(K_t, N_t\right) = A_t \left\{a\left(bK_t\right)^{\psi} + (1-a)\left[(1-b)\,N_t\right]^{\psi}\right\}^{\frac{1}{\psi}} \tag{1.18}$$

with the parameter $0 < a < 1$ and $0 < b < 1$. If $0 < \psi < 1$ and returns to scale are constant,[12] the capital factor share can be computed using Euler's theorem:

$$\alpha_t^K = ab^{\psi}\left\{ab^{\psi} + (1-a)(1-b)^{\psi}\left(\frac{K_t}{N_t}\right)^{-\psi}\right\}^{\frac{\psi-\psi^2-1}{\psi}} \tag{1.19}$$

and

$$\alpha_t^N = 1 - ab^{\psi}\left\{ab^{\psi} + (1-a)(1-b)^{\psi}\left(\frac{K_t}{N_t}\right)^{-\psi}\right\}^{\frac{\psi-\psi^2-1}{\psi}} \tag{1.20}$$

Equations (1.19) and (1.20) show that factor shares α could vary monotonically over time with capital-labor ratio $\left(\frac{K}{N}\right)$. On the other hand, Bernard and Jones (1996) observe that this monotonicity is not observed for either country- or industry-level statistics.

An alternative method is to estimate a transcendental production function (translog), introduced by Christensen et al. (1973):

$$\ln Y_t = \ln A_t + \alpha_N \ln N_t + \alpha_K \ln K_t + \beta_{NN} \ln N_t + \beta_{KK} \ln K_t \tag{1.21}$$
$$+\beta_{NK} \ln N_t \ln K_t$$

where the shares do not vary monotonically. Or, more easily, Bernard and Jones (1996) propose a new measure of technological change, the total technological productivity (TTP), for country-sector i at any point in time:

$$TTP_{i,t} = F\left(K_0, N_0, i, t\right) \tag{1.22}$$

where K_0 and N_0 are constant factors (e.g., the mean or the median) at the initial period. TTP is a counterfactual measure of the production function in which only changes in the production function itself (and not variations in quantities) are incorporated. In addition, the $\ln(TTP)$ can be written as a function of a proxy of the level of the Solow residual $\ln A_{i,t} = \alpha_{i,t} \ln\left(\frac{Y_{i,t}}{K_{i,t}}\right) + (1-\alpha_{i,t}) \ln\left(\frac{Y_{i,t}}{N_{i,t}}\right)$:

$$\ln TTP_{i,t} = \ln A_{i,t} + \alpha_{i,t} \ln K_0 + (1-\alpha_{i,t}) \ln N_0 \tag{1.23}$$

where α_0 and β_0 are the output elasticities with respect to the first year observed. Once these coefficients are known, it is possible to compute a counterfactual output, which would have been produced each year if input levels and the output elasticity factors had remained constant. Antonelli and Quatraro (2008) recently propose an index of biased TFP, $BTFP$, exploiting (1.23):

$$BTFP_{i,t} = \frac{TTP_{i,t}}{A_{i,t}} \tag{1.24}$$

If $BTTFP_{i,t}$ is different from the unity, it indicates a high level of biased technological change.

[12] For $\psi \to 0$, the production function is approaching the Cobb-Douglas form with elasticity of substitution equal to the unity; for $\psi = 1$, the production function becomes linear, $Y_t = A_t\left[abK_t + (1-a)(1-b)N_t\right]$, with infinite elasticity of substitution.

1.3.5. Growth Accounting when Technical Change is Embodied in Capital

Another important criticism of the traditional growth accounting approach is represented by the technical change embodied in capital. After a long debate,[13] the appearance of new types of capital as computers and new empirical evidence seem to confirm that the computation of TFP should take into account this type of problem. Following Hulten (1992) and assuming that prices are proportional to marginal products and constant returns to scale, the production function and the accounting identity should be modified and rewritten into

$$O_t = C_t + \Phi_t I_t = F\left(A_t, N_t, \Psi_t K_t\right) \tag{1.25}$$

where C_t and I_t are, respectively, consumption and investment, and O is the quality-adjusted output. Φ_t is the index of technical efficiency, which can be also interpreted as the best-practice level of technology during the period t and can be estimated from the ratio of the price of new investment to the price corrected for efficiency. According to Jorgenson (1966), Ψ_t is defined as the weighted average of the best-practice efficiency levels associated with each past vintage of investment, i.e.,

$$\Psi_t = \Phi_t \frac{I_t}{K_t} + \Phi_{t-1} \frac{\left(1-\delta\right) I_{t-1}}{K_t} + \Phi_{t-2} \frac{\left(1-\delta\right)^2 I_{t-2}}{K_t} + \ldots \tag{1.26}$$

. The differentiation of (1.25) leads to

$$\begin{aligned} \tfrac{\Delta O_t}{O_{t-1}} &= \left(1-\sigma_t\right) \tfrac{\Delta C_t}{C_{t-1}} + \sigma_t \tfrac{\Delta I_t}{I_{t-1}} + \sigma_t \tfrac{\Delta \Phi_t}{\Phi_{t-1}} \\ &= \left(1-\pi_t\right) \frac{\Delta N_t}{N_{t-1}} + \pi_t \frac{\Delta K_t}{K_{t-1}} + \pi_t \frac{\Delta \psi_t}{\psi_{t-1}} + \frac{\Delta A_t}{A_{t-1}} \end{aligned} \tag{1.27}$$

with σ_t and π_t, respectively, the share-weighted of consumption and investment and labor share. In this case, the term $\sigma_t \frac{\Delta \Phi_t}{\Phi_{t-1}}$ measures the extent of induced quality change in investment, while $\pi_t \frac{\Delta \psi_t}{\psi_{t-1}}$ displays the embodied technical change. Moreover, (1.27) can be rewritten in terms of unadjusted output growth $\frac{\Delta Y_t}{Y_{t-1}}$

$$\begin{aligned} \tfrac{\Delta Y_t}{Y_{t-1}} &= \left(1-\sigma_t\right) \tfrac{\Delta C_t}{C_{t-1}} + \sigma_t \tfrac{\Delta I_t}{I_{t-1}} \\ &= \left(1-\pi_t\right) \frac{\Delta N_t}{N_{t-1}} + \pi_t \frac{\Delta K_t}{K_{t-1}} + \pi_t \frac{\Delta \psi_t}{\psi_{t-1}} - \sigma_t \frac{\Delta \Phi_t}{\Phi_{t-1}} + \frac{\Delta A_t}{A_{t-1}} \end{aligned} \tag{1.28}$$

Combining (1.2) with (1.28), it is possible to rewrite the new TFP growth residual $\frac{\Delta T_t}{T_{t-1}}$ as

$$\frac{\Delta T_t}{T_{t-1}} = \pi_t \frac{\Delta \psi_t}{\psi_{t-1}} - \sigma_t \frac{\Delta \phi_t}{\phi_{t-1}} + \frac{\Delta A_t}{A_{t-1}} \tag{1.29}$$

Jorgenson (1966) shows that in the Golden-Rule-based steady-state growth, where $\pi_t = \sigma_t$ and $\frac{\Phi_t}{\Phi_{t-1}} = \frac{\Psi_t}{\Psi_{t-1}}$, the new TFP growth $\frac{\Delta T_t}{T_{t-1}}$ is reduced to the Solow residual $\frac{\Delta A_t}{A_{t-1}}$.

[13]Denison (1964) and Baily and Gordon (1988) argue the embodiment is unimportant, while Triplett (1983) and Gordon (1990), among others, provide evidence of the role played by the embodied technical change. Greenwood et al. (1997) consider a growth model that incorporates technological change specific to new investment good and find that embodied technical change in capital is the source about 30 percent output fluctuations in the US economy.

If the economy is far away from the steady-state equilibrium, the traditional growth accounting framework can lead to highly biased results.

1.4. The Econometrics of Technological Change

1.4.1. Basic Specifications

In addition to the index number approaches and DEA, several econometric techniques have been considered to model the rate of TFP growth. Among them,[14] Diewert (1976) considers the application of the dual approach introduced by Jorgenson and Griliches (1967) for a translog cost function C with input prices P_i, input quantity Q_i and input shares S_i:

$$\ln C\left(P_{1t} - \ldots P_{mt} Q_t, t\right) - \ln C\left(P_{1t-1} - \ldots P_{mt-1} Q_{t-1}, t-1\right) =$$

$$= \textstyle\sum_{i_1}^{m} \frac{S_{it}+S_{it-1}}{2} \ln \frac{P_{it}}{P_{it-1}} + \frac{1}{2}\left(\frac{\partial \ln C}{\partial \ln Q_t} + \frac{\partial \ln C}{\partial \ln Q_{t-1}}\right) \ln \frac{Q_t}{Q_{t-1}}$$

$$+\frac{1}{2}\left(\frac{\partial \ln C}{\partial t} + \frac{\partial \ln C}{\partial t-1}\right) \tag{1.30}$$

where the last term of (1.30) can be computed as a residual.

When a panel structure of the data is available, the translog cost function (1.30) can be also estimated by adding the firms' dummies D_k and the time trend T as follows:

$$\ln C = \alpha_0 + \textstyle\sum \lambda_k D_k + \sum \alpha_i \ln P_i + \gamma \ln Q + \delta T$$

$$+\tfrac{1}{2} \textstyle\sum\sum \beta_{ij} \ln P_i \ln P_j + \frac{1}{2}\gamma\left(\ln Q\right)^2 + \frac{1}{2}T^2$$

$$+\sum \phi_i T \ln P_i + \sum \psi_i \ln P_i \ln Q + \theta T \ln Q \tag{1.31}$$

Using Shepard´s lemma (Shepard (1970)), it is possible to obtain the cost shares of input i, S_i:

$$S_i = \frac{\partial \ln C}{\partial \ln P_i} = \alpha_i + \sum_j \beta_{ij} \ln P_j + \phi_i T + \psi \ln Q \tag{1.32}$$

with $i = 1, \ldots, n$. The estimation of (1.31) and (1.32) can be used to compute the rate of technical change as

$$\dot{T} = \frac{\partial \ln C}{\partial T} = \delta + \delta T + \sum \phi_i \ln P_i + \theta \ln Q \tag{1.33}$$

while the estimation of the TFP growth $\ln \widehat{\left(\frac{A_t}{A_{t-1}}\right)}$ is given by

$$\ln \widehat{\left(\frac{A_t}{A_{t-1}}\right)} = -\dot{T} + \left(1 - \epsilon_{CQ}\right) \dot{Q} \tag{1.34}$$

[14] Most of these contributions are described in Olley and Pakes (1996), Jorgenson (2001), and Aghion and Griffith (2005).

with the estimated elasticity of cost with respect to output ϵ_{CQ}. In addition to the criticisms illustrated in Section 1.5, another problem arises in the presence of the panel: while the intercept of (1.32) is allowed to vary by sector (or by industry), the other coefficients are equal across production units and over time. Next, Binswanger (1974) and Jorgenson (1986) estimate productivity from constant time trends in a translog production function with input prices as introduced by Christensen et al. (1973).

This framework has been criticized by Chambers (1988), Kopp and Smith (1983) and Gollop and Roberts (1983) from theoretical and empirical perspectives: the assumption of a linear trend does not seem realistic because it does not take into account innovations and developments and the embodiments of the new investment.[15] Next, Jorgenson and Fraumeni (1981) and Jorgenson et al. (1987) propose the introduction of nonlinear terms and interactions of the time variable with prices, allowing TFP to grow at variable rates and the production function to include increasing return to scale; Denny et al. (1981) suggest observable measures of technological change as R&D investments. Moreover, Baltagi and Griffin (1988) introduced a methodology for estimating technological change in panel data: in this case, industry and time dummies are combined in a nonlinear estimation procedure to obtain a general index of technological change. Finally, Sickles and Tsionas (2008) consider the same framework in a Bayesian setup.

1.4.2. The State-space Approach

In addition to the basic specification represented in the previous section, the state-space approach is an original and alternative econometric technique that can be implemented in the estimation of a technological change.[16] Although this framework is widely used in economics, very few studies use this tool for estimating productivity. The first contribution in this area has been introduced by Harvey and Wren-Lewis (1986), who propose this approach to model TFP in an employment-output equation, while Slade (1989) considers a translog production function and the dual approach for a micro-level application to the US primary-metals industry. Another empirical example has been illustrated by Esposti (2000), who follows a similar methodology and, using data from the Italian agriculture industry, attempts to identify the generated technical progress induced by R&D and extension expenditure. The last two models have the limitation of assuming the observability of TFP growth at time t, defined as $\ln\left(\frac{A_t}{A_{t-1}}\right)$ and represented by the fluctuation of the output Y and an unobservable "technological" part T. For discrete time, they study the following representation:

$$\ln\left(\frac{A_t}{A_{t-1}}\right) = \Gamma \ln\left(\frac{Y_t}{Y_{t-1}}\right) + \ln\left(\frac{T_t}{T_{t-1}}\right) + \epsilon \tag{1.35}$$

where Γ is a parameter to be estimated, $\epsilon \sim NIID\left(0, \Omega_\epsilon\right)$ with Ω_ϵ an $N \times N$ covariance matrix.

Another similar macroeconomic application can be found in Gordon (2003), who estimates trends for identifying *productivity bubbles* by comparing results of the Hodrick-

[15]Section 1.7 considers the problem of technological change when it is embodied in capital.
[16]A technical description of the State-space models can be found in Chapter 3.

Prescott filter with respect to the Kalman one. His approach consists of considering the following equation,

$$\ln\left(\frac{A_t}{A_{t-1}}\right) = \alpha_t + \Gamma X_t + \epsilon_t \tag{1.36}$$

where X_t is a set of explanatory variables and α_t is a time-series process for the time-varying productivity-trend, which obeys to a random walk

$$\alpha_t = \alpha_{t-1} + v_t \tag{1.37}$$

where the error term of this two equation system are $w_t \sim N\left(0, \Sigma^2\right)$ and $v_t \sim N\left(0, \tau^2\right)$. In addition, Kahn and Rich (2003) start from the Solow residual for separating labor productivity from the time trend using a combination of the Kim filter (Kim and Nelson (2001)) and a Markov switching model.

Finally, the most innovative application to be estimated using the Kalman filter technique has been introduced by Jorgenson and Jin (2008), who consider a dual approach for a translog production function, assume that technological change is not observable and model it as latent variable with the production function elasticities. More formally, they consider as a reference point for the measurement equation the following system of equations

$$\begin{cases} \ln P_{Y_t} = \alpha_0 + \alpha' \ln p_t + \frac{1}{2} \ln p_t' B \ln p_t + \ln p_t' f_t + f_{pt} + \epsilon_t^p \\ v_t = \alpha + B \ln p_t + f_t + \epsilon_t^v \end{cases} \tag{1.38}$$

where P_{Y_t} is the output price at time t, p is the vector of the input price, v is the vector of the input share, f is the vector of technology bias, and B is the matrix containing the share elasticities. In addition, for the transition equation, they consider technology vector $F = \begin{bmatrix} 1 \\ f \end{bmatrix}$ and model a VAR

$$F_t = \Phi F_{t-1} + u_t \tag{1.39}$$

where u_t is a random vector with mean zero representing technology shocks and Φ is a matrix of unknown parameters of a first-order VAR. Other studies exploiting the Kalman filter can be found in Chapter 3.

1.4.3. Parametric Methods

Parametric methods are popular in the literature for studying technological change: they estimate TFP growth from a production function, usually a Cobb-Douglas with Hicks neutral technology for firm i, industry j and time t,

$$\ln Y_{it}^j = \beta_0 + \beta_n \ln N_{it}^j + \beta_k \ln K_{it}^j + \ln TFP_{it}^j + \epsilon_{it}^j \tag{1.40}$$

where Y is the firm's output measured as value added, N is the free variable inputs labor, and K is the state variable capital. Replacing (1.40) in (1.2), it is possible to compare the measurement resulting from this estimation with the Solow residual:

$$\ln\left(\frac{A_{it}}{A_{it-1}}\right) = \ln TFP_{it} - \ln TFP_{it-1} \tag{1.41}$$

$$= \ln\left(\tfrac{Y_{it}}{Y_{it-1}}\right) - \alpha \ln\left(\tfrac{K_{it}}{K_{it-1}}\right) - (1-\alpha)\ln\left(\tfrac{N_{it}}{N_{it-1}}\right) - (\epsilon_{it} - \epsilon_{it-1})$$

The error has two non-observable components, TFP_{it}^{j}, which has an impact on the firm's decision choice, and the error term ϵ_{it}^{j}, which is uncorrelated with input choices. TFP_{it}^{j} is not observed by the researcher and can create simultaneity problems in the production function, giving inconsistent OLS results (Marschak and Andrews (1944)). As Mairesse and Grilliches (1990) note, the main limitation of these models is the assumption of the same returns to scale for all observations concentrating the entire heterogeneity in the productivity process.

Assuming that employment can be freely adjusted, the methodology introduced by Olley and Pakes (1996) and extended by Levinsohn and Petrin (2003) can avoid this problem. They treat intermediate goods used by the firm as instruments for controlling the correlations between capital and shocks. Moreover, as suggested by Barba Navaretti et al. (2008), an estimate of the production function for each sector is preferred for avoiding the strict assumption of common technology across sectors.

1.4.4. Estimation of the Spillover Effects and Endogeneity Problems

In the literature, there are two different methods to estimate spillovers, i.e. positive externalities generated by the closeness of other firms which can increase the output growth . The first one is to estimate a similar form of (1.2), adding an error term ϵ_t:

$$\frac{\Delta Y_t}{Y_{t-1}} = \beta_0 + \beta_1 \frac{\Delta K_t}{K_{t-1}} + \beta_2 \frac{\Delta N_t}{N_{t-1}} + \epsilon_t \tag{1.42}$$

where $\hat{\beta}_0$ represents the estimated TFP growth. The difference between the estimated $\hat{\beta}_1$ and the α of the Solow residual can be interpreted as a measure of the spillover effects. However, an OLS estimation can provide biased results because of endogeneity problems: Hall (1990) restates this problem, noting that *"The productivity residual is uncorrelated with any variable that is uncorrelated with the rate of growth of true productivity."* (Hall, 1990: 71). In other words, TFP tends to follow the business cycle: in years of expansion, the residual is unusually large; in years of recession, it is low or even negative. Moreover, other movements of inputs and outputs can be correlated with the stochastic shifts in the technology. Hall attempted to solve these problems rewriting the (1.2) by adding a random term ϵ_t

$$\frac{\Delta Y_t}{Y_{t-1}} - \left\{\alpha \frac{\Delta K_t}{K_{t-1}} + (1-\alpha_t)\frac{\Delta N_t}{N_{t-1}}\right\} = \frac{\Delta A_t}{A_{t-1}} + \epsilon_t \tag{1.43}$$

and estimating TFP growth using as instruments military spending, the world oil price and a dummy for indicating the political party of the US President. Furthermore, Mankiw et al. (1992) writes that the productivity level A_t is not just pure technological change, which is assumed to be constant across countries, but that country-specific components, ε_i, such as resource endowments, climate and institutions influence growth. For these reasons, they assume that $A = A_t\varepsilon_i$. However, in addition to the problem related to the endogeneity of the specification, the spillover effects can be confused with increasing returns to scale economies and/or deviations from perfect competition.

Another popular approach in the literature can be found in Stiroh (2002a) and Brynjolfsson and Hitt (2003), who estimate the following equation:

$$\begin{aligned}\Delta \ln TFP_{jt} = \beta + \beta_1 \tfrac{I^*_{jt}}{Y_{jt}} + \beta_2 \tfrac{K^*_{jt}}{Y_{jt}} + \beta_3 \ln N_t \\ + \beta_4 X_{jt} + \epsilon_{jt} \end{aligned} \tag{1.44}$$

where K^* and I^* are, respectively, the capital and the investment in the new technological good. The parameter $\beta_1 = \frac{\partial Y}{\partial K^*}$, representing the excess rate of return of the technology, can be considered as a measure of spillover. The limitation of this approach is represented by missing variables in the specification, as managerial skills or measure of organization, which are unobservable or difficult to measure. More details on these problems can be found in Chapter 4.

1.5. Data Envelopment Analysis and the Malmquist Index

The data envelopment analysis (DEA) is an alternative technique mostly used in operation research and productivity analysis and differs from the growth accounting approach for the introduction of the concept of efficiency of the use of inputs, which is placed side-by-side with the concept of technology. A detailed review on efficiency analysis is provided by Fried et al. (2008).

While the following chapters concentrate on technological change, it is useful to provide some discussion on efficiency analysis. Koopmans (1951) defines the presence of technical efficiency in a production unit with one output y and a nontrivial vector of inputs x if an increase in the output requires an increase in at least one element of x and if a reduction in any input requires an increase in at least one other input or a reduction of the output. Given a production technology T

$$T = \{(y, x) : x \ can \ produce \ y\}, \tag{1.45}$$

Debreu (1951) and Farrell (1957) introduce a measure of efficiency exploiting the input distance function, D_I, formulated by Shepard (1953) as

$$D_I(y, x) = \max\left\{\lambda : \left(\frac{x}{\lambda}\right) \in L(\lambda)\right\}, \tag{1.46}$$

where λ represents the maximum feasible reduction in all inputs given a particular technology $L(y)$, which can be represented by the input sets

$$L(\lambda) = \{x : (y, x) \in T\}. \tag{1.47}$$

In addition, after defining a production technology represented by output sets,

$$P(x) = \{y : (x, y) \in T\}, \tag{1.48}$$

Shepard (1970) also introduces an alternative representation of the production technology with the output distance function:

$$D_O(x,y) = min\left\{\lambda : \begin{pmatrix} \frac{y}{\lambda} \end{pmatrix} \in P(x)\right\}. \tag{1.49}$$

An alternative computation of the output distance for the set of inputs and outputs (x, y) can be derived by solving the following problem

$$\begin{aligned} &\inf_{\theta,\lambda\geq 0}\theta \\ s.t.\ &-y/\theta + Y^T\lambda \geq 0 \\ &x - X^T\lambda \geq 0 \end{aligned}$$

where X and Y are matrices composed of vector columns of inputs and outputs of the economy. This problem computes a set of nonnegative weights θ or multipliers λ that minimize the weighted input-to-output ratio of the technology under evaluation.

Given these definitions, input-oriented technical efficiency TE_I can be represented as the inverse of $D_I(x,y)$:

$$TE_I(y,x) = \frac{1}{D_I(y,x)} \tag{1.50}$$

Similarly, output-oriented technical efficiency is given by

$$TE_O(x,y) = \frac{1}{D_O(x,y)}. \tag{1.51}$$

1.5.1. The Malmquist Index

The *Malmquist index* M_t^{t+1} represents one of the most commonly used indices in DEA and an alternative way for computing productivity and efficiency changes in the production functions.[17] Proposed by Caves et al. (1982) reinterpreting an index introduced by Malmquist (1953), it is defined in the original version by the ratio of two distance output functions:

$$M_{CCD}^t = \frac{D_O^t(x^{t+1}, y^{t+1})}{D_O^t(x^t, y^t)} \tag{1.52}$$

where the numerator is represented by the maximal proportional change in outputs required to obtain the combination (x^{t+1}, y^{t+1}) feasible in relation to the technology at time t, while the denominator is (1.49) at time t. Färe et al. (1989) consider an alternative measure of (1.52), as

$$M_{FGLR}^{t+1} = \frac{D_O^{t+1}(x^{t+1}, y^{t+1})}{D_O^{t+1}(x^t, y^t)} \tag{1.53}$$

and propose a new version of the Malmquist index, defined as the geometric mean of (1.52) and (1.53):

$$M_0\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \left[\left(\frac{D_O^t(x^{t+1}, y^{t+1})}{D_O^t(x^t, y^t)}\right)\left(\frac{D_O^{t+1}(x^{t+1}, y^{t+1})}{D_O^{t+1}(x^t, y^t)}\right)\right]^{\frac{1}{2}}. \tag{1.54}$$

[17] For a review of the indices used in productivity analysis, see Thanassoulis et al. (2008).

In addition, Färe et al. (1992) rewrite (1.54) yielding an efficiency and a technological term:

$$M_0\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \left(\frac{D_O^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_O^t\left(x^t, y^t\right)}\right)\left[\left(\frac{D_O^t\left(x^t, y^t\right)}{D_O^{t+1}\left(x^t, y^t\right)}\right)\left(\frac{D_O^t\left(x^{t+1}, y^{t+1}\right)}{D_O^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right)\right]^{\frac{1}{2}} \tag{1.55}$$

where the term $\left[\left(\frac{D_O^t\left(x^t, y^t\right)}{D_O^{t+1}\left(x^t, y^t\right)}\right)\left(\frac{D_O^t\left(x^{t+1}, y^{t+1}\right)}{D_O^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right)\right]^{\frac{1}{2}}$ measures the contribution of technological change.

Assuming a case with one output and two inputs, it is possible to normalize by labor so as only one input in the production function, so that $y_t = \frac{Y_t}{N_t}$ and $k_t = \frac{K_t}{N_t}$. Because the Solow decomposition contains the assumption that the production is always technically efficient, the Malmquist index can be rewritten in terms of the Törnqvist decomposition as

$$M_t^{t+1} = \left[\frac{D_0^t\left(x^{t+1}, y^{t+1}\right)}{D_0^t\left(x^t, y^t\right)}\right] = \frac{A_{t+1}}{A_t}, \tag{1.56}$$

where A_t is the state of TFP as defined in Section 1.2. Figure 1.3 depicts a graphical representation of the Malmquist index for an economy in the presence of constant return to scale and full efficiency: four data points provide a measure of technology change (from T_0 to T_1), which contributes to move from point A, i.e., the amount of output produced at time 0 $y_0^0 \equiv f_0(k_0)$, to point C, i.e., the production in the second period $y_1^1 \equiv f_1(k_1)$. To do so, TFP growth is decomposed into the input accumulation and the information on the counterfactuals, point D, which represents the production using the technology at time 0 with the amount of input used at time 1 ($y_1^0 \equiv f_0(k_1)$), and point B, i.e., the amount produced with input at time 0 and technology used at time 1 ($y_0^1 \equiv f_1(k_0)$), where, for each y_i^j is the amount produced with input at time j and technology at time k. As illustrated in Chapters 2 and 3, this equivalence between the Solow residual and the technological term of the Malmquist index is useful for estimating an initial value of TFP growth.

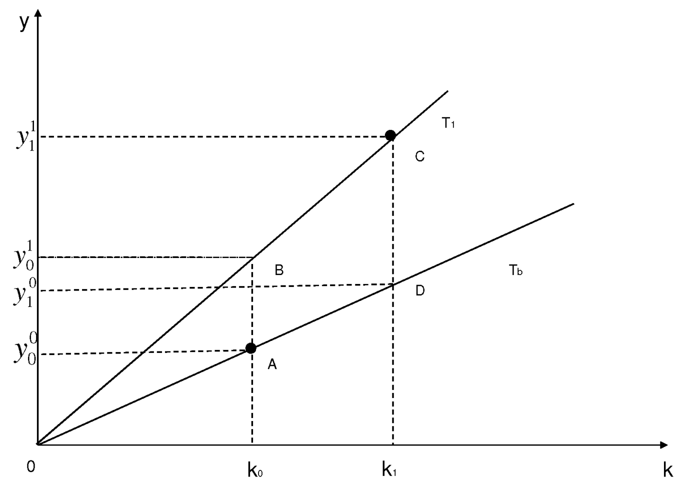
$$\xi_0 = \ln\left(\frac{A_1}{A_0}\right) = \ln\left(M_0^1\right) = \frac{1}{2}\ln\left(\frac{y_1^1}{y_0^0}\frac{y_1^0}{y_0^1}\right). \tag{1.57}$$

1.6. Conclusion

TFP growth is both a fundamental measure of economic growth and welfare at the macro economic level and is an important indicator of firm performance. In this chapter I survey the literature on the most commonly used techniques in measuring productivity. More precisely, I investigate the limits of the growth accounting and the Solow residual techniques, the econometrics of technical change and the data envelopment analysis.

One of the key building blocks of this chapter is the growth accounting technique which allows to compute the Solow residual as a difference of of the observed factor inputs and changes in factor inputs (primal approach) or as the share-weighted growth of factor prices (dual approach). The Solow residual is often used in the calculation of official statistics despite several drawbacks of this technique. First, capital measurement errors

Figure 1.3.: Different initial conditions and TFPG.



and lack of data related to capital utilization could seriously bias the computation of TFP growth. Second, the omission of spillover effects can overstate the Solow Residual. Third, if production is not Cobb-Douglas but technical progress labor-augmenting, the assumption of constant shares could seriously bias the computation of the Solow residual. Finally, if technical change is embodied in capital and the economy is far away from the steady-state equilibrium, the traditional growth accounting framework can lead to highly biased results .

I also consider several econometric techniques often used to model the rate of technological change, all of which estimate productivity as an unobservable from a production or a cost function. This chapter considers: 1) the parametric estimation of TFP growth from a production function (usually a Cobb-Douglas), 2) the estimation of translog cost function derived from the application of the dual approach, and 3) the estimation of the unobservable components of the production or cost function exploiting Kalman filter techniques. Similar to the growth accounting framework, capital measurement errors and the presence of positive externalities can bias the estimation results.

Finally, the chapter discusses the data envelopment analysis (DEA), devoting particular attention to the Malmquist index. DEA is an alternative technique frequently used in operation research and productivity analysis. DEA differs from the growth accounting approach as it introduces the efficient use of inputs, which is placed side-by-side with the concept of technology.

The results produced in this chapter lay the ground work for subsequent analysis presented in the later part of this thesis. In Chapter 2 I quantify the measurement error arising in the stock of physical capital and propose two alternative measurements of TFP growth. In Chapter 3 I introduce a new methodology based on State-space models in a Bayesian framework for estimating the technological change. In Chapter 4 I develop a new approach for identifying spillovers that emanate from new technologies on productivity combining a counterfactual decomposition derived from the main Malmquist index properties and modifying the econometric technique introduced by Machado and Mata (2005).

2. Solow Residuals without Capital Stocks (with Michael C. Burda)

Using synthetic data generated from a prototypical stochastic growth model, we explore the quantitative extent of measurement error for the Solow residual as a measure of TFP growth when the capital stock is measured with error and when capacity utilization and depreciation are endogenous. We propose two alternative measurements of TFP growth which do not require capital stocks. These alternatives exhibit a root mean squared error in realizations of the artificial economy which are as low as one-third of that of the Solow residual. As an application, we compute and compare TFP growth estimates using data from the new and old German federal states.

2.1. Introduction

In this chapter, we exploit quantitative macroeconomic theory to assess the extent of measurement error of the Solow decomposition. In particular, we use a prototypical stochastic growth model as a laboratory to study the robustness of the Solow residual computed using capital stocks constructed, as is the case in reality, from relatively short series of observed investment expenditures and an initial guess of the fundamentally unobservable capital stock. To generate these synthetic data, we consider a more general setup with endogenous depreciation or obsolescence for all capital in place. Using these synthetic data, we show that measurement problems are severe, in particular for economies still far from their steady state. This drawback of the Solow residual is thus most acute in applications in which its accuracy is most highly valued.

To deal with capital stock measurement error, we propose two alternative measurements of TFP growth. Both involve the elimination of capital stocks from the Solow calculation, while introducing their own, different sources of measurement error. The first, based on direct substitution, requires an estimate of the user cost of capital. The second, based on generalized first differences of national accounts data, requires an estimate of an initial condition for TFP growth (as opposed to an initial condition for the capital stock). In order to implement the latter approach, we improve on the choice of starting value of TFP growth by exploiting the properties of the Malmquist index. We then evaluate the extent of these competing errors in a horse race using the synthetic data described above. In almost all cases, our measures outperform the traditional Solow residual and reduce the root mean squared error in some cases by as much as two-thirds.

The rest of the chapter is organized as follows. In Section 2, we review the relationship between the Solow decomposition and the capital measurement problem. Section 3 proposes a prototypical stochastic dynamic general equilibrium model - the stochastic growth model with variable capacity utilization - as a laboratory for evaluating the quality of the Solow residual as a measure of TFP growth. In Section 4, we introduce our two alternative TFP growth calculation and present the results of a comparative quantitative evaluation of these measurements under varying assumptions concerning data available to the analyst. Section 5 applies the new methods to the federal states of Germany after unification as an unusual case of TFP growth measurement for regional economies which, while sharing a common economic environment, are presumably both close to and far from their respective steady-state paths, and for which the potential for capital mismeasurement is particularly large. Section 6 concludes.

2.2. Measurement Error, Depreciation and Capital Utilization

As remarked in Chapter 1, measurement error and the initial condition for capital stock are crucial for the computation of TFP with growth accounting. While output and employment are directly observable and readily quantifiable, capital must be estimated in a way which involves a number of controversial assumptions. The initial condition problem is identified by Caselli (2005), who applies *a fortiori* to a more general setting in which the initial value of capital is measured with error, if depreciation is stochastic, or is unobservable. Suppose that the elements of the sequence of depreciation rates $\{\delta_t\}$ move about some arbitrary constant δ. It is possible to rewrite (1.9)

$$K_{t+1} = \left[\prod_{i=0}^{t} (1-\delta_{t-i})\right] K_0 + \sum_{j=0}^{t} \left[\prod_{i=0}^{j} (1-\delta_{t-i})\right] I_{t-j}$$

as:

$$\begin{aligned} K_{t+1} &= (1-\delta)^{t+1} K_0 + \sum_{j=0}^{t} (1-\delta)^{j+1} I_{t-j} \\ &+ \left[\prod_{i=0}^{t} \frac{(1-\delta_{t-i})}{(1-\delta)} - 1\right] (1-\delta)^{j+1} K_0 \\ &+ \sum_{j=0}^{t} \left[\prod_{i=0}^{j} \frac{(1-\delta_{t-i})}{(1-\delta)} - 1\right] (1-\delta)^{t+j} I_{t-j} \end{aligned} \tag{2.1}$$

Equation (2.1) expresses the true capital stock as the sum of three components: 1) an initial capital stock, net of assumed depreciation at some constant rate δ, plus the contribution of investment $\{I_s\}_{s=0}^{t}$, also expressed net of depreciation at rate δ; 2) mismeasurement of the initial condition's contribution due to fluctuation of depreciation about the assumed constant value; and 3) mismeasurement of the contribution of all investment expenditures from period 0 to t. Each of these three components represents a potential source of measurement error. The first component contains errors involving the initial valuation of the capital stock. For the most part, the second and third components are unobservable. Ignored in most estimates of capital, they represent a potentially significant source of mismeasurement which would contaminate a Solow residual calculation.

The interaction between the depreciation of capital and capacity utilization is also important for both macroeconomic modeling. As also remarked in Section 1.3, from a growth accounting perspective, Hulten (1986) criticized the assumption that all factors are fully utilized. Time-varying depreciation rates implies changing relative weights of old and new investment in the construction of the capital stock. In dynamic stochastic general equilibrium models, the depreciation rate is generally assumed constant, despite empirical evidence to the contrary.[1] In addition, as argued by Corrado and Mattey (1997) and Burnside et al. (1995), capacity utilization is highly procyclical. While Kydland and Prescott (1988) and Ambler and Paquet (1994) introduced respectively stochastic capital utilization and depreciation, other authors (as Wen (1998) and Harrison and Weder (2006)) extend the RBC models assuming capacity utilization to be a convex, increasing function of the depreciation rate (Christiano et al. (2005)). A positive link between depreciation and capacity utilization is a central feature of the model we present in the next section.

2.3. Capital Measurement and the Solow Residual: a Quantitative Assessment

2.3.1. The Stochastic Growth Model as a Laboratory

The central innovation of this chapter is its assessment of alternative TFP growth measurement methods using synthetic data generated by a known, prototypical model of economic growth and fluctuations (see King and Rebelo (1999)). We extend the standard, neoclassical framework, in which the first and second welfare theorems hold and markets are complete, to allow for variable capacity utilization, following Greenwood et al. (1988), Burnside et al. (1995), and Wen (1998). The use of the neoclassical stochastic growth model in this research should be interpreted as a tribute to its microeconomic foundations than an endorsement of the real business cycle approach *per se*.[2] By using a well-understood model as a laboratory, we are able to assess quantitatively the limitations of the Solow residual measurement. In this section we first briefly describe this standard model and the data which it generates. Details can be found in the Appendix A.

Technology

Productive opportunities in this one-good economy evolve as a trend-stationary stochastic process. Total factor productivity $\{A_t\}$ is embedded in a standard constant returns production function in capital services and labor inputs and evolves for $t = 1, 2, \ldots$ according to

$$A_t = \psi^{t(1-\rho)} A_{t-1}^{\rho} e^{\epsilon_t} \tag{2.2}$$

where $\psi > 1$, $|\rho| < 1$, A_0 is given and ϵ_t is white noise. Output is given by the Cobb-Douglas production technology proposed by Wen (1998)

$$Y_t = A_t \left(U_t K_t\right)^{\alpha} N_t^{1-\alpha} \tag{2.3}$$

where $U_t \in (0, 1)$ denotes the utilization rate of capital ("capacity utilization").

[1] See the OECD (2001) manual on capital stock estimation.
[2] See King and Rebelo (1999) for a forceful statement of this view.

In this version of the model, output can either be consumed or invested in productive capacity ("capital"). Starting from a given initial K_0, capital evolves according to the Goldsmith equation

$$K_{t+1} = (1-\delta_t)\,K_t + I_t, \qquad t = 0, 1, \ldots,$$

where the rate of depreciation is an increasing, convex function of capacity utilization

$$\delta_t = \frac{B}{\chi} U_t^{\chi} \tag{2.4}$$

where $B > 0$ and $\chi > 1$. We depart from Wen (1998) and Harrison and Weder (2006) by adding a scale parameter B, which allows us to match both the mean and variance of the model's simulated capacity utilization to the data.

Households

Household owns capital and labor and sell factor services to firms in competitive factor markets. Facing sequences of wages $\{\omega_t\}_{t=0}^{\infty}$ and user cost of capital $\{\kappa_t\}_{t=0}^{\infty}$, the representative household chooses paths of consumption $\{C_t\}_{t=0}^{\infty}$, labor supply $\{N_t\}_{t=0}^{\infty}$, capital in the next period $\{K_{t+1}\}_{t=0}^{\infty}$, and capital utilization $\{U_t\}_{t=0}^{\infty}$ to maximize the present discounted value of lifetime utility (see e.g. Prescott (1986a), Greenwood et al. (1988), Cooley and Prescott (1995), King and Rebelo (1999)):

$$\max_{\{C_t\},\{N_t\},\{K_{t+1}\},\{U_t\}} E_0 \sum_{t=0}^{\infty} \beta^t \left\{ \ln C_t + \frac{\theta}{1-\eta} \left[(1-N_t)^{1-\eta} - 1 \right] \right\} \tag{2.5}$$

subject to an initial condition for the capital stock held by household K_0, the periodic budget restriction for $t = 0, 1, ...$

$$C_t + K_{t+1} - (1-\delta_t)K_t = \omega_t N_t + \kappa_t U_t K_t, \tag{2.6}$$

and the dependence of capital depreciation on utilization given by (2.4). The period-by-period budget constraint restricts consumption and investment to be no greater than gross household income from labor $\omega_t N_t$ and capital $\kappa_t U_t K_t$.

Firms

Firms in this perfectly competitive economy are owned by the representative household. The representative firm employs labor N_t and hires capital services $U_t K_t$ to maximize profits subject to the constant returns production function given by (2.3). Note that for the firm, capital service input is the product of the capital stock and its utilization rate; the firm is indifferent to whether these originate from extensive or intensive use of the capital stock.

First Order Conditions, Decentralized Equilibrium and Steady State

In Appendix A, we summarize the first order conditions for optimal behavior of households and firms and characterize the decentralized market equilibrium, in which this regular economy is unique. Dynamic behavior can be approximated by log-linearized versions of these equilibrium conditions around the model's unique steady state growth path. Along that path, output, consumption, investment and capital stock all grow at a constant rate $g = \psi^{\frac{1}{1-\alpha}} - 1$, while total factor productivity grows at rate $\psi - 1$. Employment, capital utilization and interest rates are trendless.

2.3.2. Construction of the Data Sets

The model was simulated as a quarterly calibration to the US economy with standard parameter values described in Appendix A. Each realization of the artificial economy is a set of time series $\{Y_t\}, \{K_t\}, \{N_t\}, \{C_t\}, \{I_t\}, \{U_t\}, \{\kappa_t\}, \{\omega_t\}$ of 1,200 observations. The initial condition for TFP (A_0) was drawn from a normal distribution with mean zero and standard deviation one and the capital stock in period zero (K_0) is set to its steady-state value; the model is allowed to run 100 periods before samples were drawn. For each realization, samples were drawn for both "mature" and for "transition" economies. A "mature economy" corresponds to data after period 700, while a transition economy consists of the same realization until period 699, when the capital stock is set at half its original value. The economy's equilibrium is then resolved with this lower initial capital stock from period 700 to 1200. In Figure 2.1 we display a representative time series realization of the mature economy in original and H-P detrended form with detrending parameter set at 1600.

The model's properties are summarized in Table 2.1 and compared with moments of the Hansen (1985) stochastic growth model as well as of the data as reported by Stock and Watson (1999) and Dejong and Dave (2007). Our benchmark model thus generates data which roughly replicates they key features of the US economy required for the evaluation of the Solow residual.

Figure 2.1.: A typical time series realization in levels and in H-P detrended form, periods 700-1000

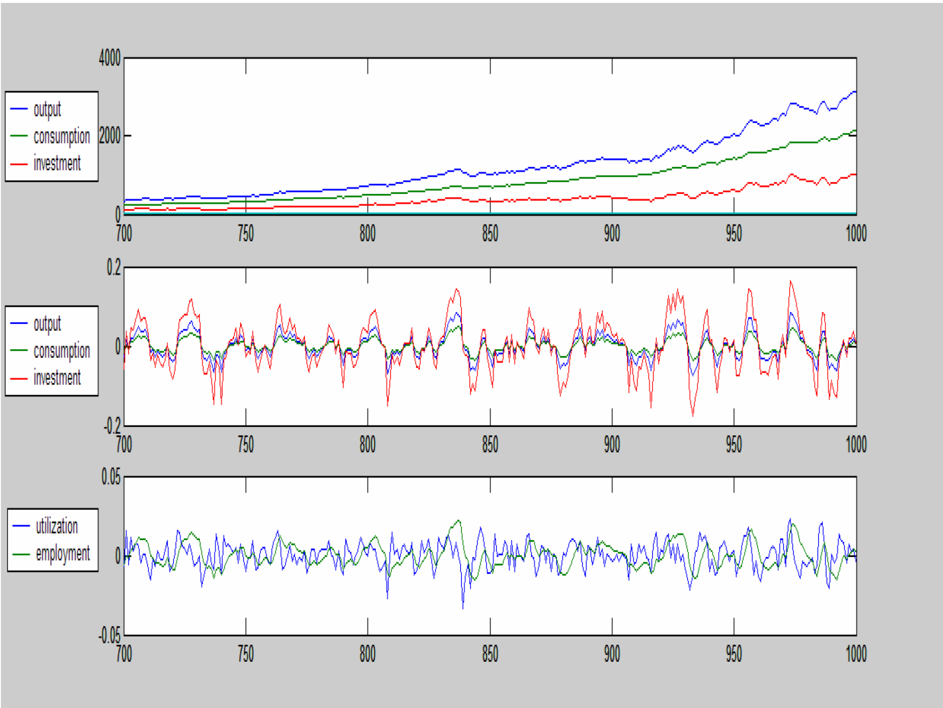


Table 2.1.: Comparative statistical properties of the model economy

Series	Benchmark model economy (200 Quarters)	Hansen (1985)		US DATA 1953Q1-1996Q4 (Stock & Watson (1999))	US DATA 1948Q1-2004Q4 (Dejong & Dave (2007))
		Divisible labor model	Indivisible labor model		
Cross-correlations with output					
Consumption	**0.99**	**0.89**	**0.87**	**0.90**	-
Investment	**1.00**	**0.99**	**0.99**	**0.89**	-
Employment	**0.48**	**0.98**	**0.98**	**0.89**	-
Productivity	**1.00**	**0.98**	**0.87**	**0.77**	-
Std. dev. normalized by std. dev. of output					
Consumption	**0.52**	**0.46**	**0.29**	**0.76**	**0.46**
Investment	**2.08**	**2.38**	**3.24**	**2.99**	**4.23**
Employment	**0.62**	**0.34**	**0.77**	**1.56**	**1.05**

2.3.3. Evaluating Measurement Error of the Solow Residual

The data generated by the model economy will now be used to investigate the precision of the Solow residual as a measurement of TFP growth. The basis of comparison is the root mean squared error (RMSE) for sample time series of either 50 or 200 observations taken from 100 independent realizations starting at period 700, for both the mature and the transition economy. The Solow residual measure is calculated as a Törnqvist index:[3]

$$\Delta \ln A_t = \Delta \ln Y_t - \bar{\alpha}_{t-1} \Delta \ln K_t - (1 - \bar{\alpha}_{t-1}) \Delta \ln N_t$$

As in reality, our central assumption is that the true capital stock data are always unobservable to the analyst, who computes them by applying the perpetual inventory method to investment data series and some initial capital stock, which is in turn estimated using various methods described above. In the baseline scenario A, the analyst is unable to observe either the rate of capacity utilization or the depreciation rate. Alternatively, we assume that the analyst can observe the utilization rate only (B) or both the utilization and the depreciation rate (C). In (B) and (C) a modified Solow residual calculation is used.[4] Caselli's measure is computed using a BEA estimate of capital K_0^* in the simulated benchmark economy, which is assumed to be at its steady state.

The results of this first evaluation are presented in Table 2.2 as the average RMSE (in percent) for each estimate. Standard errors are computed across 100 realizations and are presented in parentheses. The results show that the initial condition of the capital stock is an important source of error. Of the different methods, the BEA and Caselli approaches perform the best, yet are still characterized by significant measurement error. As would be expected, as the sample size grows, the average RMSE declines. Yet even at a sample length of 50 years (200 quarters), the annualized root mean squared error remains high at about 2%.

[3]Note that for the Cobb-Douglas production and competitive factor markets, factor shares and output elasticities are constant, so the Törnqvist Index and lagged factor share versions are equivalent.

[4]That is, $\widehat{\frac{\Delta A_t}{A_{t-1}}} = \frac{\Delta Y_t}{Y_{t-1}} - \alpha \left(\frac{\Delta K_t}{K_{t-1}} + \frac{\Delta U_t}{U_{t-1}} \right) - (1 - \alpha) \frac{\Delta N_t}{N_{t-1}}$

Table 2.2.: Avg. RMSE (%) for Solow residuals using different capital stock estimates (standard errors in parentheses).

Mature Economy (100 realizations)						
	A		B		C	
Initial capital stock estimate	**T=50**	**T=200**	**T=50**	**T=200**	**T=50**	**T=200**
-BEA	3.56	1.96	3.50	1.85	3.50	1.85
$K_0 = I_0 \frac{g+1}{g+\delta}$, g growth of investment rate	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
-Caselli (2005)/BEA	3.55	1.95	3.49	1.84	3.49	1.85
$K_0 = K_0^* \left(\frac{Y_0}{Y_0^*}\right)^{\frac{1}{\alpha}} \left(\frac{N_0^*}{N_0}\right)^{\frac{1-\alpha}{\alpha}}$	(0.26)	(0.13)	(0.27)	(0.13)	(0.28)	(0.13)
-Gollop and Jorgenson (1980)	4.98	2.62	4.94	2.54	4.94	2.54
$K_0 = I_0$	(0.04)	(0.02)	(0.03)	(0.08)	(0.03)	(0.08)
Transition Economy (100 realizations)						
	A		B		C	
Initial capital stock estimate	**T=50**	**T=200**	**T=50**	**T=200**	**T=50**	**T=200**
-BEA	4.64	2.87	1.69	1.42	3.97	2.08
$K_0 = I_0 \frac{g+1}{g+\delta}$, g growth of investment rate	(0.24)	(0.15)	(1.14)	(0.40)	(0.16)	(0.08)
-Caselli (2005)/BEA	5.26	2.76	5.27	2.78	5.28	2.79
$K_0 = K_0^* \left(\frac{Y_0}{Y_0^*}\right)^{\frac{1}{\alpha}} \left(\frac{N_0^*}{N_0}\right)^{\frac{1-\alpha}{\alpha}}$	(0.27)	(0.13)	(0.27)	(0.13)	(0.27)	(0.13)
-Gollop and Jorgenson (1980)	5.49	2.87	2.84	1.80	2.84	1.85
$K_0 = I_0$	(0.21)	(0.10)	(0.57)	(0.19)	(0.19)	(0.10)

A: Analyst observes $\{Y_t, N_t, I_t, \bar{\kappa}, \omega_t\}$ only

B: Analyst observes $\{Y_t, N_t, I_t, \bar{\kappa}, \omega_t, U_t\}$

C: Analyst observes $\{Y_t, N_t, I_t, \bar{\kappa}, \omega_t, U_t, \delta_t\}$

2.4. TFP Growth Measurement without Capital Stocks: Two Alternatives

We have shown that the Solow residual is associated with substantial measurement error. In scenario A, about 40% of this error in the short dataset is due to the estimated initial condition of the capital stock), while the rest is due to unobservable depreciation and capacity utilization. Measurement error in K_0 will bias TFPG computations when 1) depreciation is low and 2) the time series under consideration is short. For conventionally assumed rates of depreciation, errors in estimating the initial condition can have long-lasting effects on estimated capital stocks. In simulated data, it takes more than 100 periods to reach convergence within 10% of the steady state.[5] In the following two sections, we propose two capital stock-free alternatives to the Solow residual. The first, the DS method, is appropriate when the economy under analysis is far from its steady-state. The second, the GD method, relies on the economy‘s proximity to a steady-state path.

2.4.1. Direct Substitution (DS)

The first strategy for estimating TFP relies on direct substitution to eliminate the capital stock from the equation generally used to construct the Solow residual. Differentiation of the production function $Y_t = F\left(A_t, U_t K_t, N_t\right)$ with respect to time yields

$$\dot{Y}_t = F_A \dot{A}_t + F_K \dot{K}_t + F_U \dot{U}_t \ + F_N \dot{N}_t. \tag{2.7}$$

Substitution of the transition equation for capital $\dot{K}_t = I_t - \delta_t K_t$ and rearrangement yields:

$$\tfrac{\dot{Y}_t}{Y_t} = \tfrac{\dot{A}_t}{A_t} + F_K \tfrac{I_t}{Y_t} - \alpha_t \left(\delta_t + \tfrac{\dot{U}_t}{U}_t\right) + (1-\alpha_t)\tfrac{\dot{N}_t}{N}_t,$$

where α_t is, as before, the elasticity of output with respect to capital for the constant returns case. The modified version of the Solow residual is given by

$$\frac{\dot{A}_t}{A_t} = \frac{\dot{Y}_t}{Y_t} - F_K \frac{I_t}{Y_t} + \alpha_t \left(\delta_t - \frac{\dot{U}_t}{U_t}\right) - (1-\alpha_t)\frac{\dot{N}_t}{N}_t. \tag{2.8}$$

In an economy with competitive conditions in factor markets, the marginal product of capital F_K is equated to κ_t, the user cost of capital in t. This equation is adapted to a discrete time context as

$$\frac{\widehat{\Delta A_t}}{A_{t-1}} = \frac{\Delta Y_t}{Y_{t-1}} - \kappa_{t-1}\frac{I_{t-1}}{Y_{t-1}} + \alpha_{t-1}\left(\delta_{t-1} - \frac{\Delta U_t}{U_{t-1}}\right) - (1-\alpha_{t-1})\frac{\Delta N_t}{N_{t-1}}. \tag{2.9}$$

The substitution eliminates the capital stock from the TFP calculation. The DS approach will be a better measurement of TFP growth to the extent that 1) the capital stock is unobservable or poorly measured; 2) capital depreciation varies from period to period and is better measured from other sources; 3) the last gross increment to the capital stock is more likely to be completely utilized than older capital. Once TFP

[5] A graphical representation of this the impact of different inital conditions can be found in Figure 1.1 in the Chapter 1.

growth is estimated, the total contribution of capital to growth can be calculated as $\frac{\Delta Y_t}{Y_{t-1}} - \frac{\widehat{\Delta A_t}}{A_{t-1}} - (1-\alpha_{t-1})\frac{\Delta N_t}{N_{t-1}} - \alpha_{t-1}\frac{\Delta U_t}{U_{t-1}}$.

2.4.2. Generalized Differences of Deviations from the Steady State (GD)

If an economy or sector is close to its steady state, it may be more appropriate to measure growth in total factor productivity as deviations from a long-term deterministic trend path estimated using the entire available data set, e.g. trend regression estimates, moving averages or Hodrick-Prescott filtered series. If $\tilde{X}_t$ denotes the deviation of X_t around a steady state value $\overline{X}_t$, then the production function $Y_t = F(A_t, K_t, N_t)$ and the Goldsmith equation (1.8) can be approximated as

$$\tilde{Y}_t = \tilde{A}_t + s_K\left(\tilde{K}_t + \tilde{U}_t\right) + (1 - s_K)\,\tilde{N}_t \tag{2.10}$$

and

$$\tilde{K}_t = \frac{(1-\delta)}{(1+g)}\tilde{K}_{t-1} + \iota\tilde{I}_{t-1}, \tag{2.11}$$

respectively where $\iota = \frac{\overline{(I/K)}}{(1+g)}$, g is the deterministic steady state growth rate, and the capital elasticity $s_K \equiv \frac{F_K(A_t,K_t,N_t)K}{Y_t}$ is assumed constant, following the steady state restrictions on grand ratios emphasized by King et al. (1988). Multiplying both sides of (2.10) by $\left(1 - \frac{(1-\delta)}{(1+g)}L\right)$ and substituting (2.11) yields the following estimate of a generalized difference of TFP growth:

$$\left(1 - \frac{(1-\delta)}{(1+g)}L\right)\widehat{A}_t = \left(1 - \frac{(1-\delta)}{(1+g)}L\right)\widetilde{Y}_t - \iota s_K\widetilde{I}_{t-1} \tag{2.12}$$
$$-\left(1 - \tfrac{(1-\delta)}{(1+g)}L\right)s_K\widetilde{U}_t - \left(1 - \tfrac{(1-\delta)}{(1+g)}L\right)(1-s_K)\,\widetilde{N}_t$$

In (2.12) the capital stock has been eliminated completely from the computation. Given an initial condition, TFP growth estimates may be recovered recursively for the logarithmic approximation of TFP growth $t = 2, ..., T$:

$$\ln\widehat{\left(\frac{A_t}{A_{t-1}}\right)} = \Delta\theta_t + \left(\frac{1-\delta}{1+g}\right)\ln\widehat{\left(\frac{A_{t-1}}{A_{t-2}}\right)} \tag{2.13}$$

where $\Delta\theta_t = \left(1 - \frac{(1-\delta)}{(1+g)}L\right)\widetilde{Y}_t - s_K\left[\iota\widetilde{I}_{t-1} + \left(1 - \frac{(1-\delta)}{(1+g)}L\right)\widetilde{U}_t\right] - \left(1 - \frac{(1-\delta)}{(1+g)}L\right)(1-s_K)\,\widetilde{N}_t$.

The computation of productivity growth estimates using the GD procedure will thus require an estimate of the initial condition, $\ln\left(\frac{A_1}{A_0}\right)$. The one we propose is based on the Malmquist index, which we elaborate in detail in section 1.4 and in Appendix B. This estimate can be thought of the geometric mean of labor productivity growth and output growth in the first period.

2.4.3. The Need for Numerical Evaluation

The central difference between the two alternatives to the Solow residual is the point around which the approximation is taken. In the DS approach, the point of approximation is the levels of factor inputs in the previous period. In the GD approach, the point of approximation is a balanced growth path for which the capital elasticity, s_K, the growth rate g, and the grand ratio I/K are constant. The advantages and disadvantages of each measurement will depend on the application at hand. If the economy is far from the steady state, the GD is likely to yield a poor approximation. On the other hand, it is likely to be more appropriate for business cycle applications involving OECD countries. In Section 5 we will apply these TFP growth measurements as well as the Solow-Törnquist residual to the federal states of Germany, in which a case for either alternative might be made.

While both measurements eliminate capital from the TFP measurement, they introduce other forms of measurement error. The DS method subsitutes a small marginal contribution of new investment plus a depreciation which may or may not be time-varying. The capital rental price κ_t can be obtained from independent sources or economic theory, but is likely to be measured with error. Similarly, the GD procedure measures the marginal contribution of new capital but substitutes another form of measurement error (the growth of TFP in the first period). Given that the GD method necessarily assumes a constant rate of depreciation, it will tend to do worse when the depreciation rate is in fact endogenous and procyclical. It should perform poorly for economies or sector which are far from their steady states. In the end, it is impossible to see which type of measurement error is lower without resorting to simulation methods. This is what we do in the next section.

2.4.4. Assessing Alternative Measures of TFP Growth: a Horse Race

We now employ the same artificial data produced by the stochastic growth model in Section 2.1 to compare the most precise versions of the Solow residual calculation, which estimate initial capital stocks along the lines of the BEA (Reinsdorf and Cover (2005), Sliker (2007)) and Caselli (2005), with our two alternative measurements. It is important to state carefully the assumptions behind the construction of the TFP growth measures. As before, the analyst is assumed never to observe the true capital stock, but does observe gross investment, employment, GDP, and real wages in each period. Under alternative scenarios, the analyst can or cannot observe the rate of capacity utilization or the depreciation rate in each period. When not observable, a constant quarterly value of the depreciation rate was assumed, equal to 0.015. For the DS method, we assume that the analyst cannot observe the user cost of capital (κ_t) in each period, but rather uses a constant $\bar{\kappa}$, its average value over the entire sample realization. For the GD estimates computed using equation (2.13), values of the constants δ and ι are set equal to 0.015 and 0.0112. respectively. We employed the Malmquist index described to estimate the initial condition of TFP growth as described in Chapter 1 and in Appendix B.

As in the previous section, the basis of comparison is the root mean squared error (RMSE) for sample time series of 50 or 200 observations taken from 100 independent realizations of the stochastic growth model described in Section 2.1. The RMSE of this horse race along with standard errors are presented in Table 2.3 for both the "mature" economy (first panel) as well as the "transition economy" (second panel).

The horse race suggests that elimination of the capital stock is associated with substantial improvement of the quality of TFP growth measurement over the conventional Solow residual. This improvement is significant for samples of both 50 and 200 observations, and for both mature and traditional economies. The DS outperforms both alternatives under all assumptions, and by as much as 63% (BEA versus DS, T=50). For the GD approach, the estimate of initial TFP growth based on of the Malmquist index makes a substantial contribution to RMSE compared with assuming $\ln\left(\frac{A_1}{A_0}\right) = 0$.[6]

[6]We also considered the Malmquist index, described in Chapter 1, itself as an alternative measure of TFP in each period. We obtained very similar, but inferior, results compared with the GD method.

Table 2.3.: A horse race: Stock-less versus traditional Solow-Törnquist estimates of TFP growth.

Mature economy (100 realizations, standard errors in parentheses)						
	A		B		C	
TFP growth estimates	**T=50**	**T=200**	**T=50**	**T=200**	**T=50**	**T=200**
-Direct Substitution (DS)	0.90	0.89	0.64	0.64	0.65	0.64
	(0.10)	(0.06)	(0.09)	(0.04)	(0.09)	(0.04)
-Generalized Differences (GD)	2.62	2.57	2.21	2.14	2.19	2.12
	(0.19)	(0.11)	(0.14)	(0.08)	(0.20)	(0.07)
-Solow Residual/BEA	3.56	1.96	3.50	1.85	3.50	1.85
estimate of K_0	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
-Solow Residual/Caselli (2005)/BEA	3.55	1.95	3.49	1.84	3.49	1.85
estimate of K_0	(0.26)	(0.13)	(0.27)	(0.13)	(0.28)	(0.13)
Transition economy (100 realizations, standard errors in parentheses)						
	A		B		C	
TFP growth estimates	**T=50**	**T=200**	**T=50**	**T=200**	**T=50**	**T=200**
-Direct Substitution (DS)	3.22	1.78	1.50	1.33	2.34	1.31
	(0.22)	(0.10)	(0.67)	(0.18)	(0.11)	(0.08)
-Generalized Differences (GD)	4.85	3.40	1.75	1.72	3.08	2.55
	(0.35)	(0.15)	(1.31)	(1.21)	(0.21)	(0.09)
-Solow Residual/BEA	4.64	2.87	3.16	1.89	3.97	2.08
estimate of K_0	(0.24)	(0.15)	(1.14)	(0.40)	(0.03)	(0.02)
-Solow Residual/Caselli (2005)/BEA	5.26	2.76	5.27	2.78	5.28	2.79
estimate of K_0	(0.27)	(0.13)	(0.27)	(0.13)	(0.27)	(0.13)

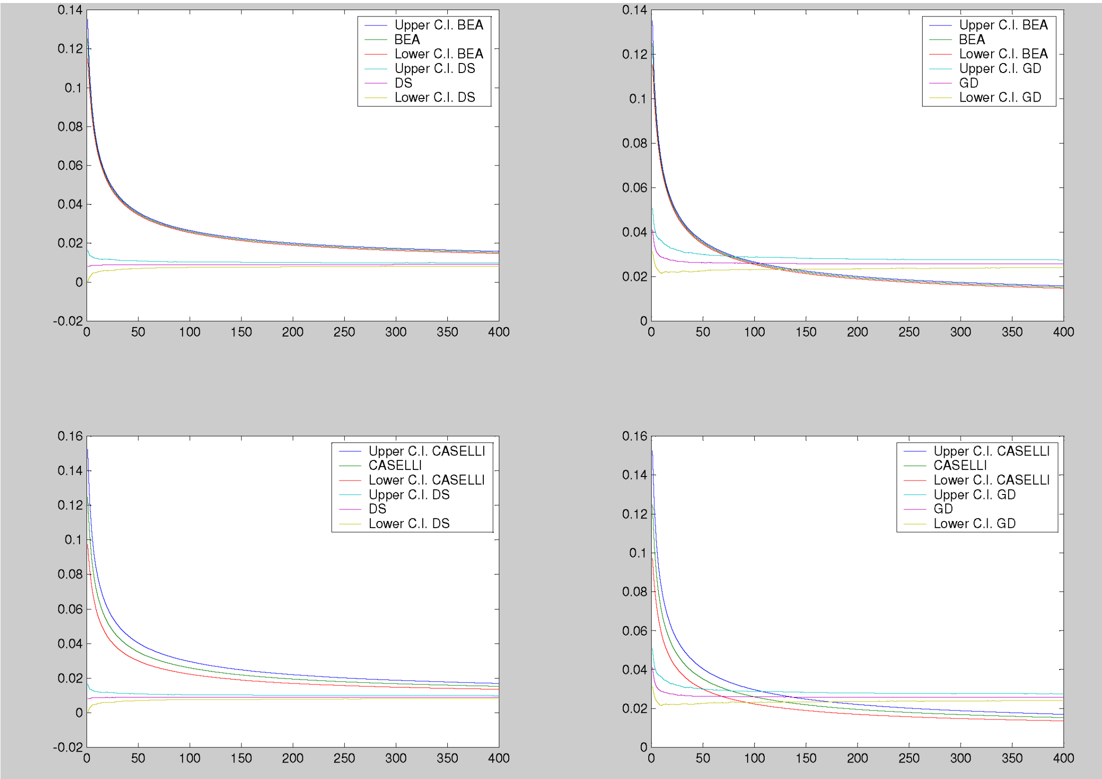
A: Analyst observes $\{Y_t, N_t, I_t, \bar{\kappa}, \omega_t\}$ only

B: Analyst observes $\{Y_t, N_t, I_t, \bar{\kappa}, \omega_t, U_t\}$

C: Analyst observes $\{Y_t, N_t, I_t, \bar{\kappa}, \omega_t, U_t, \delta_t\}$

As would be expected, the RMSE improvement of the stock-less measures over the conventional Solow residual estimates is inversely related to the relative importance of the initial condition and thus to the length of the sample time series. This relationship in our synthetic data set is displayed in Figure 2.2, which presents four comparisons of average RMSE for the mature economy case, along with confidence bands of two-standard deviation, as a function of the sample size from the same 100 realizations of 1,200 (quarterly) observations. The graphs demonstrate how the stock-less measurements perform significantly better in a root mean squared error sense for a small sample, and that this advantage tends to die out at a slow rate. At a sample size of 400 or more observations - a century of data - are the two equally accurate).

Figure 2.2.: Dependence of RMSE (%) on sample size (with two standard error bands)



2.5. Application: TFP growth in the German federal States

We now apply the two new TFP growth measures to study the source of economic growth in the federal states of Germany after reunification. To this purpose, GDP and "national" income account data are available beginning with 1991 for 16 states: 11 "old" Western states (Bavaria, Baden-Württemberg, Bremen, Hamburg, Hesse, Lower Saxony, North Rhine-Westphalia, Rhineland-Palatinate, Saarland, Schleswig-Holstein), 6 "new" Eastern states (Berlin, Brandenburg, Mecklenburg-West Pommerania, Saxony-Anhalt, Saxony, and Thuringia).[7] We employ the income and product accounts and capital stock estimates at the level of the federal states published by the Working Group for State Income and Product Accounts (*Arbeitsgemeinschaft Volkswirtschaftliche Gesamtrechnung der Länder*).[8] This dataset allows us to revisit the findings of Burda and Hunt (2001), who assessed divergent evolution of labor productivity and total factor productivity between East and West and within the two groups of states using the conventional Solow residual measure and their crude own estimates of the states' capital stocks. Given the poor measurement of the capital stock in the new states, especially for structures, the alternative DS and GD methods offer an opportunity to investigate TFP growth measurements with a "treatment" group (East Germany) as well as a "control" group (West Germany), where the treatment is an unusually bad measurement of initial capital stocks. Reunification - due to both market competition and the revaluation of the east German mark - rendered about 80% of East German production noncompetitive (Akerlof et al. (1991)), implying a large loss of value of existing equipment and structures. At the same time, many structures measured initially at minimal book value have been re-employed by businesses, implying higher value of the capital stock than conventionally measured. Depreciation rates and capacity utilization data do not exist at the level of the *Bundesland*, further compounding already severe measurement problems.

In Table 2.4, we present Solow-Törnqvist residuals and our stock-free TFP measurements for both new and old German states averaged over two sub-periods 1994-1999 and 2000-2006. We also present the same calculations based on macroeconomic aggregates constituted by the Eastern states, the Western and all of Germany. The Solow residual estimates utilize an estimate of capital stocks provided by the state (*Bundesland*) statistical agencies and the working group involved in collecting and standardizing the state income and product accounts. A constant capital share (0.33) was assumed. For the DS method, the annual rental price of capital (κ) was set to a constant value over the entire period at a value of 0.11. For the GD approach, a simple two-sided moving average of three years was used to estimate the trend. For both approaches, a constant rate of capital depreciation δ equal to 7.52% per annum was employed. Capacity utilization and depreciation at the *Bundesland* level is not meaured, so the equivalent of scenario A was adopted throughout. Lacking data on hours worked, we used total employment as a measure of labor input.

We first turn to the TFP growth estimates for the aggregated regions East, West and all Germany. With one exception, the qualitative predictions of the DS and GD measures are consistent with those of the Solow residual, which indicate a pick-up of TFP growth over the period in the East and a decline in the West. However, as time series the DS and GD estimates are considerably less volatile than the Solow residual; the coefficient of variation for the period 1994-2006 were 0.42 and 0.48 for the former, respectively, compared with 0.78 for the latter. To the extent that all three measures

[7] Berlin is counted as a new state consisting of the union of East and West Berlin, because the western half of Berlin, while under the protection and economic aegis of Western Germany until 1989, never enjoyed full status as a *Bundesland*.

[8] The data can be downloaded at the website `http://www.vgrdl.de/Arbeitskreis_VGR/ergebnisse.asp`. Capital stocks for the new states in the period 1991-1993 were computed by backcasting the perpetual inventory method from the 1994 estimates.

are estimating the same phenomenon, the alternative we propose appear to provide a tighter estimate of the temporal evolution of TFP in the two regions.

The same conclusion can be drawn from the cross-sectional dimension of our TFP measurements. The prior expectation we bring to the exercise is that measurement error should be most severe in the new states, given the limited basis for computing capital stocks there. Yet there is little reason to expect wide variation across space within the East or West during during these seven-year intervals. Indeed, the coefficients of variation for Solow residuals in the East are almost an order of magnitude larger than the DS and GD estimates in the early period 1994-1999 (5.0 versus 0.9 and 0.3). In the latter half of the sample, the coefficients of variation of the three measures are similar across the East-West divide (0.7, 0.4, and 0.2 for Solow, DS, and GD in the East, versus 0.7, 0.4, 0.3 in the West, respectively). The consistently lower coefficients of variation of the alternative measures in cross section is further evidence that our measures provide more accurate measurement of TFP growth.

The DS and GD estimates can be used to back out an implied contribution of capital to real growth, or, given a capital share, to growth in the "true" (i.e. actually utilized) capital stock. These estimates are presented in Tables 2.5 and 2.6. They indicate indeed a larger degree of fluctuation than implied by official estimates of capital stock growth. They support the findings of Burnside et al. (1995) and others, that the fluctuation of capital in use is an important source of measurement error and should be considered carefully when computing the Solow residual. The GD and DS measures exclude this source of mismeasurement to the extent that the utilization of recent capital formation more closely tracks the "true" utilization rate. It is striking that both alternative measurements imply virtually no contribution of growth in capital service to evolution of East German GDP in the latter period, despite impressive investment rates in the 1990s (Burda and Hunt (2001)).

Table 2.4.: TFP Measurement in German Federal States: A Comparison

	Solow Residual		**DS**		**GD**	
	1994-1999	2000-2006	1994-1999	2000-2006	1994-1999	2000-2006
Berlin	0.1	-0.2	0.4	0.7	1.9	1.0
Brandenburg	0.7	1.0	1.8	1.7	4.4	2.1
Mecklenburg-Western Pomerania	-0.4	0.7	0.1	1.2	4.9	2.1
Saxony	-0.3	1.7	1.3	2.4	4.6	2.0
Saxony-Anhalt	-1.0	1.4	0.1	2.1	3.8	1.8
Thuringia	0.2	1.5	1.0	2.2	4.0	1.8
All East German states	**0.4**	**1.0**	**0.8**	**1.7**	**3.4**	**1.6**
Baden-Württenberg	1.6	0.8	2.7	1.6	1.8	1.0
Bavaria	1.4	1.4	2.5	2.2	1.0	0.7
Bremen	1.5	1.6	2.8	2.7	1.8	1.1
Hamburg	0.9	0.0	2.5	0.3	1.2	0.9
Hesse	1.4	0.8	2.6	1.6	1.3	0.8
Lower Saxony	0.5	0.5	1.5	1.2	0.5	0.2
North Rhine-Westphalia	0.7	0.4	1.9	1.3	1.6	0.8
Rhineland-Palatinate	0.5	0.4	1.5	1.1	1.0	0.5
Saarland	0.9	1.6	1.8	2.3	2.0	1.0
Schleswig-Holstein	0.7	0.6	1.7	1.5	1.2	0.7
All West German states	**1.0**	**0.8**	**2.2**	**1.6**	**1.3**	**0.7**
Germany	**1.0**	**0.8**	**2.0**	**1.6**	**1.6**	**0.8**

Table 2.5.: Growth accounting using the three methods, 1994-1999 (% per annum).

	$\frac{\Delta Y}{Y}$	$(1-\alpha)\frac{\Delta N}{N}$	$\frac{\Delta A}{A}$	$\frac{\Delta K}{K}$	$\frac{\Delta A^{DS}}{A^{DS}}$	$\alpha\frac{\Delta K^{DS}}{K^{DS}}$	$\frac{\Delta A^{GD}}{A^{GD}}$	$\alpha\frac{\Delta K^{GD}}{K^{GD}}$
Berlin	-0.3	-0.9	0.1	0.5	0.4	0.2	1.9	-1.3
Brandenburg	4.8	0.2	0.7	3.9	1.8	2.8	4.4	0.1
Mecklenburg-Western Pomerania	4.5	0.2	-0.4	4.8	0.1	4.3	4.9	-0.5
Saxony	4.3	0.3	-0.3	4.2	1.3	2.6	4.6	-0.7
Saxony-Anhalt	3.7	-0.4	-1.0	5.0	0.1	3.9	3.8	0.3
Thuringia	4.4	0.4	0.2	3.7	1.0	3.0	4.0	0.0
All East German states	**3.0**	**0.0**	**0.4**	**2.6**	**0.8**	**2.3**	**3.4**	**-0.4**
Baden-Württenberg	2.2	0.3	1.6	0.3	2.7	-0.7	1.8	0.1
Bavaria	2.3	0.3	1.4	0.6	2.5	-0.5	1.0	1.0
Bremen	1.0	-0.6	1.5	0.0	2.8	-1.3	1.8	-0.3
Hamburg	1.1	-0.2	0.9	0.4	2.5	-1.1	1.2	0.2
Hesse	1.8	0.0	1.4	0.3	2.6	-0.8	1.3	0.5
Lower Saxony	1.3	0.4	0.5	0.4	1.5	-0.7	0.5	0.3
North Rhine-Westphalia	1.2	0.3	0.7	0.2	1.9	-1.1	1.6	-0.8
Rhineland-Palatinate	1.4	0.5	0.5	0.4	1.5	-0.5	1.0	-0.1
Saarland	1.7	0.5	0.9	0.3	1.8	-0.6	2.0	-0.8
Schleswig-Holstein	1.4	0.2	0.7	0.5	1.7	-0.5	1.2	0.0
All West German states	**1.7**	**0.3**	**1.0**	**0.4**	**2.2**	**-0.8**	**1.3**	**0.1**
Germany	**1.9**	**0.2**	**1.0**	**0.7**	**2.0**	**-0.3**	**1.6**	**0.1**

Note: Components may not add exactly due to rounding error.

Table 2.6.: Growth accounting using the three methods, 2000-2006 (% per annum).

	$\frac{\Delta Y}{Y}$	$(1-\alpha)\frac{\Delta N}{N}$	$\frac{\Delta A}{A}$	$\frac{\Delta K}{K}$	$\frac{\Delta A^{DS}}{A^{DS}}$	$\alpha\frac{\Delta K^{DS}}{K^{DS}}$	$\frac{\Delta A^{GD}}{A^{GD}}$	$\alpha\frac{\Delta K^{GD}}{K^{GD}}$
Berlin	-0.4	-0.3	-0.2	0.1	0.7	-0.7	1.0	-1.1
Brandenburg	1.2	-0.8	1.0	1.1	1.7	0.3	2.1	-0.1
Mecklenburg-Western Pomerania	0.7	-0.8	0.7	0.8	1.2	0.3	2.1	-0.7
Saxony	1.7	-0.6	1.7	0.7	2.4	0.0	2.0	0.4
Saxony-Anhalt	1.0	-1.0	1.4	0.6	2.1	-0.1	1.8	0.3
Thuringia	1.6	-0.9	1.5	1.0	2.2	0.3	1.8	0.7
All East German states	**0.9**	**-0.7**	**1.0**	**0.6**	**1.7**	**-0.1**	**1.6**	**0.0**
Baden-Württenberg	1.6	0.3	0.8	0.4	1.6	-0.4	1.0	0.3
Bavaria	2.2	0.3	1.4	0.5	2.2	-0.3	0.7	1.2
Bremen	1.8	0.0	1.6	0.2	2.7	-0.9	1.1	0.7
Hamburg	1.3	0.0	0.8	0.4	1.6	-0.4	0.8	0.4
Hesse	1.2	0.3	0.0	1.0	0.3	0.6	0.9	0.0
Lower Saxony	1.2	0.1	0.8	0.3	1.6	-0.5	0.8	0.3
North Rhine-Westphalia	1.1	0.2	0.5	0.4	1.2	-0.3	0.2	0.6
Rhineland-Palatinate	0.8	0.1	0.4	0.3	1.3	-0.6	0.8	-0.1
Saarland	1.1	0.3	0.4	0.4	1.1	-0.4	0.5	0.2
Schleswig-Holstein	1.9	0.2	1.6	0.1	2.3	-0.6	1.0	0.7
All West German states	**0.9**	**0.0**	**0.6**	**0.3**	**1.5**	**-0.6**	**0.7**	**0.2**
Germany	**1.4**	**0.2**	**0.8**	**0.4**	**1.6**	**-0.4**	**0.7**	**0.4**

Note: Components may not add exactly due to rounding error.

2.6. Conclusion

Over the past half-century, the Solow residual has achieved widespread use in economics and management as a measurement of total factor productivity. Its popularity can be attributed to its simplicity and independence from statistical methods. Despite this acceptance, there has been no effort to evaluate systematically the quality of this measurement tool. This complacency is remarkable in light of potentially severe measurement problems associated with capital stock data. We have documented the significance of this error, as measured by the root mean squared error is in a synthetic data set. Application of our TFP growth measures to the federal German states after reunification yields results which are more stable across time and in cross section.

While the measurement error of the Solow residual decreases with sample size, it remains especially acute for short data sets or economies in transition. Thus, the Solow residual is least accurate in applications for which TFP measurements are most valuable. Such applications the transition to a market economy, the introduction of ICT capital in the production process, and the increasing employment of weightless assets such as advertising goodwill and research and development knowledge (Corrado et al. (2006)).

Both of our proposed alternatives to the Solow-Törnqvist measures can be thought of as a "marginalization" of the error carried forward by the capital stock across time. Most recent investment is most likely to be properly valued at acquisition cost and to be fully utilized. Our results suggest that these methods could be applied to a number of investment context and types, thus widening the scope and appeal of applied TFP measurement.

3. State-space Models, Technological Change, and Initial Conditions

Several econometric techniques consider the level of technology as an unobservable or latent variable in a neoclassical production function. In this chapter, I propose a new methodology based on State-space models in a Bayesian framework. This econometric procedure provides highly accurate results with the advantage that capital series, which are often affected by measurement errors, are unnecessary. Moreover, applying the Kalman Filter to artificial data, I propose a computation for the initial condition of TFP growth based on the properties of the Malmquist index. Comparing the results using the Gibbs-sampler, I find that the root mean squared error of this procedure can be two-thirds lower than the Solow residual when it is computed following the standard growth accounting procedure. In addition, I extend this framework to panel data. The empirical application focuses on Danish industry data. The comparison between the TFP growth measures provided by the Danish national statistics and the Kalman filter estimations suggest that capital can play an important role in estimating technological change, especially in industries where it is more difficult to obtain a precise measure of the inputs.

3.1. Introduction

Chapter 2 demonstrated that it is possible for measurement error in inputs to provide ambiguous TFP growth results in the growth accounting approach, where technological change is computed as a residual between the growth rate of output and inputs. Though this methodology has been widely used in productivity analysis over the last 50 years, econometric techniques have had a recent revival, especially in studies on the effects of the income distribution. This is because such techniques estimate the level of technology, which is considered an unobservable or a latent variable in neoclassical production functions. More specifically, econometric techniques have been used to study the skill-biased technological change (Acemoglu (2002)) and the role played by technology in environmental climate change (Jaffe et al. (2003)). However, as previously stated in chapters 1 and 2, these estimation techniques can also be affected by capital measurement errors.

This chapter is devoted to the study of a new methodology based on State-space models in a Bayesian framework, proposing an innovative method of improving the estimation of technological change, especially when capital is affected by measurement errors and industry panel datasets are considered. This technique will have several possible applications due to the recent creation of the so-called *KLEM* datasets, i.e., new databases containing measures of economic growth, productivity, employment creation, and capital formation at the industry level for the US (constructed by Jorgenson et al.

(2005)), Europe (the *EU KLEMS*), and Eastern Asia (the databases collected by the Japanese Research Institute for Economy, Trade and Industry (RIETI) for China, Japan, South Korea and Taiwan).[1] Given the availability of these data, Nakamura and Diewert (2007) provide some theoretical arguments showing that capital measurement errors can be relevant not only at the aggregate level, but at the industry level as well. One of the most striking examples is represented by the retail sector: in this case, national statistical offices do not usually consider important capital assets such as land, whose regulation plays an important role in countries like the UK (Griffith and Harmgart (2005)), and inventories, leading to biased TFP growth estimates.

Another important issue is related to the relationship between productivity and the role played by the so-called *New Economy* in the last 15 years. Although the official statistics suggest that the service sector was the most important contributor to the TFP boom of the 1990s (Basu et al. (2004)), the amount of capital is hard to measure in this industry due to questionable assumptions not only on the depreciation rate but also on the definition of inputs. Moreover, as Gordon (2000) and Nordhaus (2002) point out, one cause of the acceleration of productivity growth after 1995 could be attributed to a continuous and rapid decline in the price of ICT goods, contributing to a boom in investment in new information and communication technologies. Further, obtaining a precise measure for capital could be particularly difficult in this case because of the intangible nature of these assets. More precisely, studying industry level data, Griliches (1994) distinguishes between sectors where output and input are well measured. Such a distinction can be attributed to several factors. First, especially in service sector industries such as retail and banking, the price indexes of deflating goods and services may not be fully representative because these industries have a wide range of types of output.[2] Second, in sectors where ICT goods are largely used, as with the example of retail, it is quite difficult to measure changes in quality, especially for products newly introduced in the market.

In this chapter, after describing the setup of the State-space model, I propose an alternative measurement of TFP growth for industry data based on a Kalman filter framework. This methodology does not require capital stocks, but an initial value for technological change. Several techniques are implemented for computing initial TFP growth, including the maximum likelihood estimation (MLE) and the Gibbs-sampler. Similar to Chapter 2, I improve on the choice of the starting value of TFP growth by exploiting the properties of the Malmquist index. Furthermore, I evaluate the RMSE of the different techniques in a horse race considering artificial data, computed by a standard RBC model, showing that the root mean squared of this procedure can also be two-thirds lower than the Solow residual when capital contains a measurement error.

[1] These datasets can be found at the following links: `http://dvn.iq.harvard.edu/dvn/dv/jorgenson/faces/study/StudyPage.xhtml?studyId=18782&studyListingIndex=0_9a34a24ecd962a7c49ed76ef9a95` (US KLEMS), `www.euklems.net` (EU KLEMS), and `http://www.rieti.go.jp/en/database/index.html` (RIETI dataset).

[2] Griliches (1994) itself addresses this point in the following way: *"Imagine a degrees of measurability scale, with wheat production at one end and lawyer services at the other. One can draw a rough dividing line on this scale between what I shall call "reasonably measurable" sectors and the rest, where the situation is not much better today than it was at the beginning of the national income accounts."*

In addition, I extend this framework to a panel data structure. This empirical application focuses on Danish industry data: after investing for the stationary properties of the data, I compare the TFP growth provided by the Danish statistical offices with the results of the Kalman filter errors, suggesting that for some particular industry, where inputs are more difficult to define, capital measurement could be an important issue. In addition, this problem seems to be greater during the *New Economy* period.

This chapter is structured as follows. Section 2 reviews the literature on State-space models and proposes the Kalman filter representation for measuring TFP growth. Section 3 introduces the initial condition problem and analyzes the techniques based on a maximum likelihood estimation, Gibbs-sampling, and the Malmquist index. In Section 4, I introduce the basic RBC standard model. Section 5 compares the different approaches to estimating the TFP growth initial condition. Section 6 provides the results applied to the artificial data. Section 7 analyzes the stationarity properties of the time series and applies the new method to data on Danish industries. Section 8 concludes the chapter.

3.2. The State-space Representation and TFP Measurement

In this chapter, I propose an innovative method estimating TFP growth using a State-space framework, also known as Kalman filter, as introduced by Kalman (1960) and described in detail by Hamilton (1994). The Kalman filter can be defined as a dynamic time-series model in which an observable variable can be expressed as the sum of a linear function of some observable and unobservable variables plus an error. Furthermore, the unobservable variables evolve according to a stochastic difference equation. The paths of these observable and unobservable variables are inferred from the data. This framework can be combined with Bayesian techniques that allow shifts in the parameters that describe the dynamics of the system.

The use of the State-space approach to estimate TFP growth and capital stocks is not new to the literature; in addition to the studies already described in Section 1.4, other econometric procedures that employ this approach are worth mentioning. For example, considering the real business cycle model introduced by Greenwood et al. (1988), DeJong et al. (2000) estimate a Bayesian autoregressive model in which the ratio of productivity to its steady state value is one of the unobservable variables that evolves following a stochastic difference equation. A different approach is suggested by Hall and Basdevant (2002) and Basdevant (2003), who propose a technique based on the Kalman filter for obtaining estimates of the capital stock of the Russian economy during the transition period 1994-1998. They assume that productivity is a constant obtained from an estimate of a Cobb-Douglas production function and that the depreciation rate contains some measurement errors. Another innovative framework is that of Jorgenson and Jin (2008), who consider a dual approach to a translog production function. They assume that technological change is not observable and model it as a latent variable with production function elasticities. Finally, Chen and Zadrozny (2009) make a recent contribution to the literature by considering both productivity and capital as unobservables.

With respect to the previous literature, this chapter provides two innovations: first, the observation equation is derived from the standard growth accounting decomposition and is completely free of measurement error in the capital stock, which is substituted by investment series; second, unlike the approach proposed by Chen and Zadrozny (2009), where an initial condition is needed both for TFP growth and capital, I propose an initial condition for productivity only.

In this section, I follow the procedure adapted for a Bayesian framework suggested by Kim and Nelson (2001). A State-space model is represented by two equations: an observation and a transition equation. The observation equation describes the relationship between the observable and the unobserved state variables of the model and is usually expressed in the following form:

$$y_t = H_t \xi_t + A x_t + \epsilon_t, \tag{3.1}$$

where y_t, an $n \times 1$ vector of explanatory variables observed at time $t = 1, 2, \ldots, T$, is related to the measurable data, represented by the $r \times 1$ vector x_t of exogenous or predetermined observed variables and ξ_t, a $k \times 1$ vector of unobserved state variables. H_t is a $n \times k$ matrix that links y_t and ξ_t, while A is $1 \times k$ vector, which relates the observable variable with the exogenous one.

The transition equation represents the dynamics of the state variables and can be modeled as a first-order difference equation in the state vector:

$$\xi_t = \tilde{\mu} + F \xi_{t-1} + v_t \tag{3.2}$$

where $\tilde{\mu}$ is a $k \times 1$ vector of the constant, while the error terms ϵ_t and v_t, with the respective dimensions $n \times 1$ and $k \times 1$, are normally distributed as follows:

$$\epsilon_t \sim NIID\,(0, R) \tag{3.3}$$

and

$$v_t \sim NIID\,(0, Q) \tag{3.4}$$

with the shocks uncorrelated at all lags:

$$E\left(\epsilon_t v_s^{'}\right) = 0 \tag{3.5}$$

3.2.1. Observation Equation and Törnqvist Index

The Kalman filter can be exploited as a flexible tool for evaluating TFP growth when some inputs are affected by measurement errors. Starting from the observation equation (3.1), a natural candidate for representing the relationship between observable output growth, $\frac{\Delta Y_t}{Y_{t-1}}$, inputs growth, $\frac{\Delta K_t}{K_{t-1}}$ and $\frac{\Delta N_t}{N_{t-1}}$, and the unobservable productivity, $\frac{\Delta A_t}{A_{t-1}}$, can be represented by the Solow decomposition:

$$\frac{\Delta Y_t}{Y_{t-1}} = \frac{\Delta A_t}{A_{t-1}} + \bar{s}^K \frac{\Delta K_t}{K_{t-1}} + \bar{s}^N \frac{\Delta N_t}{N_{t-1}} \tag{3.6}$$

In this case, the unobservable variable is represented only by technological change, while the shares $\bar{s}^i$ are considered known. The production function can also exhibit non-unity returns to scale, i.e., $\bar{s}^K + \bar{s}^N \neq 1$. In addition, Diewert (1976) notes that if all inputs and the output could be perfectly observed and implemented in a translog production function, the growth accounting decomposition would not contain any error terms because the residual is an exact measure of productivity. In this case, similar to the problem described in chapters 1 and 2, I assume that capital is observable but affected by some biases, caused by measurement errors due to bad estimations on the initial capital value or the depreciation rate. One strategy to correct these measurements error is to treat capital growth as an additional unobservable variable and rewrite (3.6) such that this variable does not appear. Similar to the procedure adopted for the GD method in Section 2.3.2, I propose a measure considering the deviations from a steady-state value. In so doing, I log-linearize the Goldsmith equation

$$K_t = (1-\delta)\, K_{t-1} + I_{t-1} \tag{3.7}$$

with respect to the steady-state variable $\bar{I}$ and $\bar{K}$ obtaining

$$\bar{K}\left(\ln K_t - \ln \bar{K}\right) = \bar{I}\left(\ln I_{t-1} - \ln \bar{I}\right) + (1-\delta)\,\bar{K}\left(\ln K_{t-1} - \ln \bar{K}\right) \tag{3.8}$$

Then, taking the first difference of (3.8), I obtain the following autoregressive process

$$\ln\left(\frac{K_t}{K_{t-1}}\right) = \frac{\bar{I}}{\bar{K}} \ln\left(\frac{I_{t-1}}{I_{t-2}}\right) + (1-\delta)\ln\left(\frac{K_{t-1}}{K_{t-2}}\right) \tag{3.9}$$

which can be rewritten, adding an error term $\epsilon^1 \sim (0, \sigma^2)$, as an approximation in the following way:

$$(1-(1-\delta)\,L)\ln\left(\frac{K_t}{K_{t-1}}\right) \cong \frac{\bar{I}}{\bar{K}} \ln\left(\frac{I_{t-1}}{I_{t-2}}\right) + \epsilon_t^1 \tag{3.10}$$

where L is the lag operator. The introduction of the error term can be justified by measurement errors in the initial condition and/or in the depreciation rate.

Finally, the original Törnqvist decomposition is transformed by multiplying both sides of (3.6) by $(1-(1-\delta)\,L)$ and using (3.10),

$$\begin{aligned}\ln\left(\frac{Y_t}{Y_{t-1}}\right) &= (1-\delta)\ln\left(\frac{Y_{t-1}}{Y_{t-2}}\right) + \ln\left(\frac{A_t}{A_{t-1}}\right) - (1-\delta)\ln\left(\frac{A_{t-1}}{A_{t-2}}\right)\\ &+\bar{s}_t^K \frac{\bar{I}}{\bar{K}} \ln\left(\frac{I_{t-1}}{I_{t-2}}\right) + \bar{s}_t^N \ln\left(\frac{N_t}{N_{t-1}}\right) + \bar{s}_t^N (1-\delta)\ln\left(\frac{N_{t-1}}{N_{t-2}}\right) + \epsilon_t^1 \end{aligned} \tag{3.11}$$

or, in the following matrix form:

$$\begin{aligned}\ln\left(\tfrac{Y_t}{Y_{t-1}}\right) &= (1-\delta)\ln\left(\tfrac{Y_{t-1}}{Y_{t-2}}\right) + \begin{bmatrix} 1 & -(1-\delta) \end{bmatrix} \begin{bmatrix} \ln\left(\frac{A_t}{A_{t-1}}\right) \\ \ln\left(\frac{A_{t-1}}{A_{t-2}}\right) \end{bmatrix}\\ &+ \begin{bmatrix} \bar{s}_t^K \frac{\bar{I}}{\bar{K}} & \bar{s}_t^N & \bar{s}_t^N (1-\delta) \end{bmatrix} \begin{bmatrix} \ln\left(\frac{I_{t-1}}{I_{t-2}}\right) \\ \ln\left(\frac{N_t}{N_{t-1}}\right) \\ \ln\left(\frac{N_{t-1}}{N_{t-2}}\right) \end{bmatrix} + \epsilon_t^1 \end{aligned} \tag{3.12}$$

This representation offers several advantages: first, it substitutes capital with investment series such that it is possible to perform this analysis exploiting only measured variables; second, it is possible to consider non-constant variables of the depreciation rates; finally, it allows the estimation of the shares $\bar{s}^i$ via a maximum likelihood estimation.

3.2.2. The Transition Equation

The transition equation (3.2) determines the vector of latent variables and can be modeled in several ways. Given an initial condition ξ_0 and an estimate of the unknown parameters of the coefficient $\tilde{\mu}$ and F, this equation is employed in projecting the vector of the latent productivity growth ξ_t. Because the unobservable variable in the representation of the measurement equation in (3.12) is represented by the TFP growth rate, an ideal representation of the transition equation can be

$$\ln\left(\frac{A_t}{A_{t-1}}\right) = \nu + F\ln\left(\frac{A_{t-1}}{A_{t-2}}\right) + \epsilon_t^2 \tag{3.13}$$

which can be written in a matrix form as

$$\begin{bmatrix} \ln\left(\frac{A_t}{A_{t-1}}\right) \\ \ln\left(\frac{A_{t-1}}{A_{t-2}}\right) \end{bmatrix} = \begin{bmatrix} \zeta \\ 0 \end{bmatrix} + \begin{bmatrix} \beta & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \ln\left(\frac{A_{t-1}}{A_{t-2}}\right) \\ \ln\left(\frac{A_{t-2}}{A_{t-3}}\right) \end{bmatrix} + \begin{bmatrix} \epsilon_t^2 \\ 0 \end{bmatrix} \tag{3.14}$$

This autoregressive form follow Harvey (1989a) and Slade (1989), who assume that the growth of TFP behaves as a random walk with drift ζ and coefficient β estimated and differs from the usual framework presented in RBC models, where the level of productivity dynamics follows an AR(1) (King and Rebelo (1999)). Even if the stochastic process governing technological change expressed by (3.13) with $\beta = 1$ is supported by empirical evidence on US aggregate data provided (Ireland (2001)), I prefer to estimate β using maximum likelihood estimations to exploit (3.14) and consider the usual autoregressive in the stochastic growth model illustrated in Section 4.

3.2.3. The Matrix Representation

Finally, a useful representation of the State-space model can be written in the following way:

$$y_t = \begin{bmatrix} \ln\left(\frac{Y_t}{Y_{t-1}}\right) \end{bmatrix}, H_t = \begin{bmatrix} 1 & -(1-\delta) \end{bmatrix}, \xi_t = \begin{bmatrix} \ln\left(\frac{A_t}{A_{t-1}}\right) \\ \ln\left(\frac{A_{t-1}}{A_{t-2}}\right) \end{bmatrix} \tag{3.15}$$

$$A = \begin{bmatrix} \bar{s}_t^K \frac{\bar{I}}{K} & \bar{s}_t^N & \bar{s}_t^N (1-\delta) & (1-\delta) \end{bmatrix}, x_t = \begin{bmatrix} \ln\left(\frac{I_{t-1}}{I_{t-2}}\right) \\ \ln\left(\frac{N_t}{N_{t-1}}\right) \\ \ln\left(\frac{N_{t-1}}{N_{t-2}}\right) \\ \ln\left(\frac{Y_{t-1}}{Y_{t-2}}\right) \end{bmatrix}, \epsilon_t = \begin{bmatrix} \epsilon_t^1 \end{bmatrix} \tag{3.16}$$

and

$$F = \begin{bmatrix} \beta & 0 \\ 1 & 0 \end{bmatrix}, \tilde{\mu} = \begin{bmatrix} \zeta \\ 0 \end{bmatrix}, v_t = \begin{bmatrix} \epsilon_t^2 \\ 0 \end{bmatrix} \tag{3.17}$$

3.2.4. Computation of the Kalman Filter and Maximum Likelihood Estimation

The estimation of the Kalman filter is based on two procedures: prediction and updating. These techniques are used to estimate the set of parameter χ considering a maximum likelihood estimator. The log-likelihood function, based on the normal distribution, is computed as in Hamilton (1994), and by the following recursive process:

$$\max_{\theta} l\left(\chi | Y_T\right) = \max_{\theta} \sum_{t=1}^{T} N\left(y_t | \hat{y}_{t|t-1}, V_{t|t-1}\right) \tag{3.18}$$

with $Y_t = \left(y_t^{'}, y_{t-1}^{'}, \ldots, y_1^{'}, x_t^{'}, x_{t-1}^{'}, \ldots, x_1^{'}\right)$ consisting of the observations up to time t and the mean $\hat{y}$

$$\hat{y}_{t|t-1} = E\left(y_t | Y_{t-1}\right)$$

and the variance P

$$P_{t|t-1} = E\left[\left(y_t - \hat{y}_{t|t-1}\right)\left(y_t - \hat{y}_{t|t-1}\right)^{'}\right].$$

In greater detail, after writing the State-Space form and expressing the initial values of $\xi_{0|0}$ and $P_{0|0}$, I can implement the MLE and predict and update the Kalman Filter by computing and iterating the following equations:

Basic Filtering

Prediction

The prediction considers the information from the previous period for estimating the unobserved variable at time t.

$$\xi_{t|t-1} = \tilde{\mu} + F\xi_{t-1|t-1} \tag{3.19}$$

$$P_{t|t-1} = FP_{t-1|t-1}F^{'} + Q \tag{3.20}$$

$$\eta_{t|t-1} = y_t - y_{t|t-1} = y_t - H_t\xi_{t|t-1} - Ax_t \tag{3.21}$$

$$f_{t|t-1} = HP_{t-1|t-1}H^{'} + R \tag{3.22}$$

Updating

The updating procedure combines the information obtained by the prediction with current observations.

$$\xi_{t|t} = \xi_{t|t-1} + K_t\eta_{t|t-1} \tag{3.23}$$

$$P_{t|t} = P_{t|t-1} - K_t H_t P_{t|t-1} \tag{3.24}$$

where $K_t = P_{t|t-1} H_t' f_{t|t-1}'$ is the Kalman gain.

3.3. The Initial Condition Problem

The State-space model can be estimated following the maximum likelihood technique. This type of maximization requires an initial value for the unknown variable of (3.2), i.e., the TFP growth at time 0 $\xi_0 = \ln\left(\frac{A_1}{A_0}\right)$ as opposed to the initial value for the capital stock. More formally, looking at the estimation of the TFP growth, the initial condition problem in a State-space model implies a different approach with respect to the choice of the initial value using the Törnqvist index:

1. **Törnqvist index/Solow residual problem**: In the Solow decomposition, I consider the function $f : R_+^4 \to R$, whose domain is based on $\hat{K}_0$ and $\{I_t, Y_t, N_t\}_{t=0}^{\infty}$, where the value $\hat{K}_0$ substitutes the unobservable initial capital K_0 and the image is ξ_t;

2. **State-space model**: In this case, I study the function $f : R_+^4 \to R$, whose domain is based on $\hat{\xi}_0$ and $\{I_t, Y_t, N_t\}_{t=0}^{\infty}$, where the estimated value $\hat{\xi}_0$ substitutes the unobservable productivity growth ξ_0 and the image is ξ_t.

The use of a correct initial value for technological change is also widely present in growth literature: for example, Baumol (1996) demonstrates that initial TFP growth is important to explain economic growth in general, while Blanchard and Kremer (1997) analyze the effect of the initial value of economic growth on the disorganization of the Transition countries. In the next subsections, I illustrate two different approaches to computing the initial condition, based on Maximum Likelihood and Gibbs-sampler approaches, and I compare them in a framework based on the Malmquist index.

3.3.1. The Econometric Approach

In the econometric literature, two approaches are usually considered for estimating an initial condition from time series: one is based on a maximum likelihood estimation (MLE) approach and the other studies the eigenvalues of the matrix F of (3.2).

The Rosenberg Algorithm

One way to estimate the matrix F and ξ_0 using the MLE approach is to implement the method suggested by Rosenberg (1973) and described by Harvey (1989b) and Harvey and Wren-Lewis (1986), who consider the initial value of the unobservable and its covariance matrix, P to be equal to 0, i.e., ξ_0^* and $P = 0$, which can be used to compute a set of prediction error vectors, $v_1^*, v_2^*, \ldots, v_T^*$, where

$$v_t^* = \ln\left(\frac{Y_t}{Y_{t-1}}\right) - Ax_t - F\xi_{t|t-1} \tag{3.25}$$

For a generic value of $\tilde{\xi}_0$, the Kalman filter begins with $\xi_0 = \tilde{\xi}_0$ and $P_0 = 0$ and yields $v_1, v_2, \ldots, v_T$. Because $\xi_0^* = 0$, the initial state vector of the unobservable can be rewritten as

$$\xi_0 = \xi_0^* + \xi^0 \tag{3.26}$$

Applying the prediction of basic filtering,

$$\xi_{1|0} = \tilde{\nu} + F\xi_0 = \tilde{\nu} + F\xi_0^* + F\xi_0 \tag{3.27}$$

which can be split into two parts:

$$\xi_{t+1|t} = \xi_{t+1|t}^* + G_1\xi_0, \ t = 1, \ldots, T-1 \tag{3.28}$$

where G_t is recursively calculated in the following way:

$$G_t = \left(Gt + 1 - K_t^{'}Z_t\right) G_{t-1}, \ t = 1, \ldots, T-1 \tag{3.29}$$

with $G_0 = F_1$.

The prediction error can also be split into two parts:

$$v_t = y_t - Z_t\xi_{t|t-1}^* - F_tG_{t-1}\xi_0 - \tilde{\mu} = v_t^* - F_tG_{t-1}\xi_0, \ t = 1, \ldots, T \tag{3.30}$$

Substituting the value of v_t in the likelihood function and differentiating with respect to ξ_0, I obtain the maximum likelihood estimator ξ_{0ML},

$$\xi_{0ML} = \left[\sum_{t=1}^{T} G_{t-1}^{'}Z_t^{'}F_t^{-1}Z_tG_{t-1}\right]^{-1} G_{t-1}^{'}Z_t^{'}F_t^{-1}v_t \tag{3.31}$$

Expression (3.31) is the MLE of ξ_0, conditional on the other parameters in the model, which can be expressed as

$$\ln L = -\tfrac{1}{2}\textstyle\sum_{t=1}^{T} \ln|F_t| - \tfrac{1}{2}\sum_{t=1}^{T}\left[v_t^{'} - Z_tG_{t-1}\xi_0\right]^{'} F^{-1}\left[v_t^* - Z_tG_{t-1}\xi_0\right] =$$

$$-\frac{1}{2}\sum_{t=1}^{T}\ln|F_t| - \frac{1}{2}\sum_{t=1}^{T} v_t^{'}F_t^{-1}v_t^{'} + \frac{1}{2}\xi_0^{'}\sum_{t=1}^{T} G_t^{'}Z_t^{'}F_t^{-1}v_t^* \tag{3.32}$$

Unfortunately, this MLE approach cannot be directly implemented for the industry analysis if some of the eigenvalues are greater than one. In this case, initial conditions cannot be drawn from the unconditional distribution and $\xi_{1|0}$ should be replaced with a "wild" guess on the initial value of ξ_1, with $P_{1|0} = \kappa * I$ and κ large, where the matrix $P_{1|0}$ is a positive definite matrix summarizing the guess: the larger the diagonal, the higher the uncertainty. Furthermore, Hamilton (1994) suggests computing an initial condition based on the OLS estimation of (3.11) and (3.13). Even if the unit root tests in Section 3.7 suggest that data are stationary, this approach could be biased, especially when the time series are too short, as in the case of industry data.

The Eigenvalues Procedure

Canova (2007) suggests an alternative method, where the estimation of the initial condition consists of studying the eigenvalues of the matrix F. If they are all less than one in absolute value, i.e., they are all inside the unit circle, then the variance-covariance matrix P_t is covariance-stationary and the unconditional mean can be set as

$$E\left(\xi_{t+1}\right)=\tilde{\mu}+FE\left(\xi_t\right) \tag{3.33}$$

and

$$P_t=E\left(\xi_{t+1}\xi_{t+1}^{'}\right)=E\left[\left(F\xi_t+v_{t+1}\right)\left(\xi_t^{'}F^{'}+v_{t+1}^{'}\right)\right]=$$
$$FE\left(\xi_t\xi_t^{'}\right)\left(F^{'}+E\left(v_{t+1}v_{t+1}^{'}\right)\right) \tag{3.34}$$

with

$$vec\left(P\right)=\left(I-\left(F\otimes F^{'}\right)^{-1}\right)vec\left(Q\right) \tag{3.35}$$

This approach is similar to that of Jorgenson and Jin (2008), who assume $\tilde{\mu}$ and time stationarity for American industry data, setting all the values for the initial technological level equal to 0. One way to avoid the MLE procedure is to make a "wild" guess on $\xi_{0|0}$ and assign a very large value to the diagonal elements of $P_{0|0}$. Another approach is to assume $\xi_{0|0}$ as a vector of additive hyperparameters to be estimated and, in this case, $P_{0|0}$ should be set equal to a $k\times k$ matrix of 0s using the MLE. However, these approaches could be sensitive to the choice of the guess. For these, reasons, I prefer to follow Canova (2007), who suggests to estimate (3.32) using the Rosenberg's algorithm and to modify the matrix F in $F_1=\begin{bmatrix}\beta & \epsilon_{12}\\ 1 & \epsilon_{22}\end{bmatrix}$ with small ϵ_{12} and ϵ_{22}, and with $\epsilon_{12}\neq\epsilon_{22}$ for making the computation of (3.32) feasible if $\beta=1$.

3.3.2. A Bayesian Procedure: the Gibbs-sampler

A Bayesian procedure is represented by the Gibbs-sampler, which consists in finding the posterior distribution for ξ partitioned as $(\xi_0;\xi_t)$ with $t\neq 0$. I draw from the conditional posterior distribution $p\left(\xi_0|\xi_t,y\right)$ and $p\left(\xi_t|\xi_0,y\right)$ and I apply, as a Markov Chain Montecarlo algorithm, the Gibbs-sampler following this procedure:

1. I choose an arbitrary initial value ξ_0^0;
2. For any iteration $i=1,\ldots,S$, taking as given ξ_t^{i-1}, I draw ξ_0^i from the conditional distribution Ξ_0 given $\Xi_1=\xi_1$, $p\left(\xi_0|\xi_t^{i-1},y^T\right)$;
3. I draw ξ_t^i from the conditional distribution Ξ_2, given $p\left(\xi_t|\xi_0,y^T\right)$;
4. I move to iteration $i+1$ to step 2 until I do not get some stability in the robustness of the results.

Also in this case, the proposed model cannot be directly estimated by the Gibbs-sampler described in Section 3.3 because the covariance matrix in (3.4) Q is not positive-definitive. For these reasons, I follow the modification proposed by Kim (1994), who considers the first $J\times J$ block of this matrix as positive semi-definitive, denoted by $Q*$. The steps of the modification are as follows:

1. I estimate the State-space model as illustrated in the previous section and store the entire value of $\xi_{T|T}$ and $P_{T|T}$.
2. I compute ξ^*_{t+1} and $P_{t|t,\xi^*_{t+1}}$ as
$$\xi^*_{t+1} = F^*\xi_t + v^*_{t+1} \tag{3.36}$$
3. Find the update equations as
$$\xi^*_{t|t,\xi^*_{t+1}} = \xi_{t|t} + P_{t|t}F^{*'}\left(F^*P_{t|t}F^{*'} + Q^{*'}\right)^{-1}\left(\xi^*_{t+1} - \tilde{\mu} - F^*\xi_{t|t}\right) \tag{3.37}$$
$$P_{t|t,\xi^*_{t+1}} = P_{t|t} - P_{t|t}\left(F^*P_{t|t}F^{*'} + Q^{*'}\right)^{-1}F^*P_{t|t} \tag{3.38}$$

I consider 10,000 iterations, providing a certain level of robustness to the results, as shown in Section 3.6.

3.3.3. The Malmquist Index Approach and Growth Accounting

An alternative method of computing the initial value for TFP growth can be obtained by considering the same procedure based on the Malmquist index from period 0 to 1 as a measure of initial TFP growth, as already described in Chapters 1 and 2; i.e.,
$$\ln M_0^1 = \frac{1}{2}\ln\left(\frac{y_1^1}{y_0^0}\frac{y_1^0}{y_0^1}\right) = \underbrace{\frac{1}{2}\ln\left(\frac{y_1^1}{y_0^0}\right)}_{KNOWN} + \underbrace{\frac{1}{2}\ln\left(\frac{y_1^0}{y_0^1}\right)}_{UNKNOWN} \tag{3.39}$$

The Malmquist index offers the advantage of placing a bound on the possible evolution of TFP from period 0 to period 1, considering first the extreme case in which there is no capital accumulation in period 0, i.e., $k_0 = k_1$ and $\ln M_0^1 = \frac{1}{2}\ln\left(\frac{y_1^1}{y_0^0}\right)$; in the other extreme, capital accumulation is identical to the growth of labor productivity, i.e. $\ln M_0^1 = \ln\left(\frac{y_1^1}{y_0^0}\right)$.

Exploiting the eventual panel structure of the data, (3.39) can be rewritten in the following way:
$$\ln M_0^1 = \frac{1}{2}\ln\left(\frac{Y_1/N_1}{Y_0/N_0}\right) + \frac{1}{2}\ln\left(\frac{Y_0^*/N_1}{Y_1^*/N_0}\right) \tag{3.40}$$
where Y^* represents the output of another industry that has similar characteristics with respect to the unit of production studied. The new ratio, which combines different outputs with inputs, could be considered a good approximation for considering similar technologies.

Chapter 1 describes several techniques for computing an initial value for capital. Given the results provided by Table 2.3, I choose the methodology suggested by BEA, i.e., the investment in the initial period I_0, represents the steady state in which expenditures grow at rate g and are depreciated at rate δ, so a natural estimate of K_0 is given by $I_0\left(\frac{1+g}{\delta+g}\right)$. This is the preferred procedure because it provides the best results and is easily implementable in the case of industry data.

3.4. The Stochastic Growth Model

Similar to the procedure illustrated in Chapter 2, I consider a neoclassical stochastic growth model for assessing quantitatively the limitations of the standard growth accounting procedure and the importance of the initial condition. In this case, I assume full capacity utilization, a constant depreciation rate and there is no trend-stationary processes. More details of the model can be found in Appendix C.

Technology

The level of TFP A_t, which provides the shocks of the models evolves following the following stationary stochastic AR(1) process

$$\ln A_{t+1} = \rho \ln A_t + \epsilon_t \tag{3.41}$$

where $\{\epsilon_t\}$ is a Gaussian white noise, the initial A_0 is given and $|\rho| < 1$. One single output is produced by a Cobb Douglas production technology

$$Y_t = A_t \left(K_t^{\alpha} N_t^{1-\alpha} \right) \tag{3.42}$$

Households

A representative household maximizes the present discounted value of lifetime utility receiving income from labor N and capital K. Government does not play any role. Given the sequences of wages $\{\omega_t\}_{t=0}^{\infty}$ and user cost of capital $\{\kappa_t\}_{t=0}^{\infty}$, the representative household chooses paths of consumption $\{C_t\}_{t=0}^{\infty}$, labor supply $\{N_t\}_{t=0}^{\infty}$, capital in the next period $\{K_{t+1}\}_{t=0}^{\infty}$, and capital utilization $\{U_t\}_{t=0}^{\infty}$ to maximize the present discounted value of lifetime utility

$$\max_{\{C_t\},\{N_t\},\{K_{t+1}\}} E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln C_t + \ln N_t \right] \tag{3.43}$$

subject to an initial condition for the capital stock held by household K_0, the periodic budget restriction for $t = 0, 1, ...$

$$C_t + K_{t+1} - (1-\delta) K_t = \omega_t N_t + \kappa_t K_t, \tag{3.44}$$

the time constraint

$$L_t + N_t = 1 \tag{3.45}$$

The period-by-period budget constraint restricts consumption and investment to be no greater than gross household income from labor $\omega_t N_t$ and capital $\kappa_t U_t K_t$.

Firms

Firms in this perfectly competitive economy are owned by the representative household. The representative firm employs labor N_t and hires capital services K_t to maximize profits subject to the constant returns production function given by (3.42).

First Order Conditions, Decentralized Equilibrium and Steady State

In Appendix C, I summarize the first order conditions for optimal behavior of households and firms and characterize the decentralized market equilibrium, in which this regular economy is unique. Dynamic behavior can be approximated by log-linearized versions of these equilibrium conditions around the model's unique steady state.

3.4.1. Construction of the Data Sets

The model was simulated as a quarterly calibration to the US economy with standard parameter values described in Appendix C. Each realization of the artificial economy is a set of time series $\{Y_t\}, \{K_t\}, \{N_t\}, \{C_t\}, \{I_t\} \{\kappa_t\}, \{\omega_t\}$ of 1,200 observations. The initial condition for TFP (A_0) was drawn from a normal distribution with mean zero and standard deviation one and the capital stock in period zero (K_0) is set to its steady-state value; the model is allowed to run 100 periods before samples were drawn.

Table 3.1.: Comparative statistical properties of the model economy

Series	**Benchmark model economy (200 Quarters)**	**Hansen (1985)**		**US DATA 1953Q1-1996Q4 (Stock & Watson (1999))**	**US DATA 1948Q1-2004Q4 (Dejong & Dave (2007))**
		Divisible labor model	**Indivisible labor model**		
Std. dev. normalized by std. dev. of output					
Consumption	**0.68**	**0.46**	**0.29**	**0.76**	**0.46**
Investment	**2.00**	**2.38**	**3.24**	**2.99**	**4.23**
Employment	**0.25**	**0.34**	**0.77**	**1.56**	**1.05**

The standard deviation of the model normalized by the standard deviation of output are compared with the same moments of the Hansen (1985) stochastic growth model as well as of the data provided by Stock and Watson (1999) and Dejong and Dave (2007). The RBC model thus generates data which are quite similar to the characteristics of the US economy.

3.5. Horse Race Results

I now consider the artificial data generated by the stochastic growth model described in Section 3.4. I consider 10,000 simulations and a period of 35 observations. Figure 3.1 compares the distribution for the initial TFP growth computed with the Malmquist Index (upper part) and the Gibbs-sampler (lower part) for the 10,000 iterations and suggests that a good guess for the initial condition of TFP growth should be different from 0, indicating that the methodology proposed by Hamilton (1994) cannot be directly applied here.

Table 3.2 displays the RMSE in %. The horse race suggests that the State-space models with the initial condition for TFP growth using the Gibbs-sampler and the Malmquist index approach can reduce the RMSE by one-half and three quarters, respectively. Moreover, it is worth noting that the ML estimation with the Rosenberg technique performs poorly and the results are similar to the traditional Solow Residual.

3.6. State-space Model with Panel Structure

In this section, I propose a new version of the State-space model that can be adapted to the panel structure. With the underlying assumption that several models of production with different technologies are present at different points in time, I can consider a panel of different industries for a country and rewrite the State-space equation represented by (3.11) and (3.14) as:

$$\ln\left(\frac{Y_{i,t}}{Y_{i,t-1}}\right) = (1-\delta)\ln\left(\frac{Y_{i,t-1}}{Y_{i,t-2}}\right) + \begin{bmatrix} 1 & (1-\delta) \end{bmatrix} \begin{bmatrix} \ln\left(\frac{A_{i,t}}{A_{i,t-1}}\right) \\ \ln\left(\frac{A_{i,t-1}}{A_{i,t-2}}\right) \end{bmatrix}$$
$$+ \begin{bmatrix} \bar{s}^K_{i,t}\frac{\bar{I}_i}{K_i} & \bar{s}^N_{i,t} & \bar{s}^N_{i,t}(1-\delta) \end{bmatrix} \begin{bmatrix} \ln\left(\frac{I_{i,t-1}}{I_{i,t-2}}\right) \\ \ln\left(\frac{N_{i,t}}{N_{i,t-1}}\right) \\ \ln\left(\frac{N_{i,t-1}}{N_{i,t-2}}\right) \end{bmatrix} + \epsilon^1_{i,t}$$

and

$$\begin{bmatrix} \ln\left(\frac{A_{i,t}}{A_{i,t-1}}\right) \\ \ln\left(\frac{A_{i,t-1}}{A_{i,t-2}}\right) \end{bmatrix} = \begin{bmatrix} \zeta_{i,t} \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \ln\left(\frac{A_{i,t-1}}{A_{i,t-2}}\right) \\ \ln\left(\frac{A_{i,t-2}}{A_{i,t-3}}\right) \end{bmatrix} + \begin{bmatrix} \epsilon^2_{i,t} \\ 0 \end{bmatrix} \tag{3.46}$$

with industry $i = 1, 2, \ldots, N$ and time $t = 1, 2, \ldots, T$.

While the observation equation can be easily constructed and estimated, particular attention should be paid to the transition equation. This panel VAR can be written in more concisely as

$$\xi^i_t = \tilde{\mu}^i_t + F\xi^i_{t-1} + \epsilon_t, \tag{3.47}$$

and in particular on the object $\tilde{\mu}_t^i = \begin{bmatrix} \zeta_{i,t} \\ 0 \end{bmatrix}$.

In addition, the literature dealing with panel-data proposes different strategies to find the precise initial condition. For example, microeconometric studies try to find instruments to correct the potential measurement errors (Arellano and Bond (1991)). In contrast, from a macroeconometric point of view, Cogley and Sargent (2005) and Sargent et al. (2006) set the initial belief using an OLS estimation from pre-sample data. This strategy has been criticized by Sims (2000) because the estimation could provide some information on the steady state of the economy that is wholly different from the required initial condition[3] and he proposes a Bayesian estimation that offers a flat prior as the best choice. Furthermore, Lee and Schmidt (1993) consider this parameter as time-varying; however, the estimation of the model is infeasible if the number of $N \times T$ parameters is large. Finally, Canova and Ciccarelli (2004) prefer to treat $\tilde{\mu}_t^i$ as a fixed effect, i.e., $\zeta_{it} = \zeta_i$. Though all of these techniques are widely used, in this State-space model, I prefer a Bayesian estimation and follow the reverse engineering approach in the procedure utilized by Lancaster (2002).

3.6.1. Reverse Engineering

Reverse engineering is based on a technique introduced by Schotman and van Dijk (1991)[4] that considers the probability given by $Prob\,(data|\zeta)$ and (3.47), which is necessary to find a convergent estimation for ζ and ξ_0^i through the Gibbs-sampling procedure for a panel structure with N industries (with N larger than time T). Using Bayesian inference and assuming $|\zeta| \neq 1$, the initial condition is randomly drawn from the unconditional distribution

$$\xi_0^i \sim N\left(\frac{\tilde{\mu}_i}{1-\zeta}, \frac{\sigma^2}{1-\zeta}\right) \tag{3.48}$$

Then, using the Gibbs-sampler, I iterate to get the conditional probability for ζ given the data:

$$Prob\,(\zeta|data) \propto \sigma^{-NT}\Pi_{i=1}^{N}\int_{-\infty}^{\infty} exp\left\{-\left(\frac{1}{2\sigma^2}\right)\sum_{i}^{N}\left(\xi_t^i - \tilde{\mu}_i - F\xi_{t-1}^i\right)'\left(\xi_t^i - \tilde{\mu}_i - F\xi_{t-1}^i\right)\right\}\pi\,(\zeta) \tag{3.49}$$

which can be rewritten as

$$Prob\,(\zeta|data) \propto \sigma^{-NT}\prod_{i=1}^{N}\exp-\left(\frac{1}{2\sigma^2}\right)\sum_{i}^{N}\left(\xi_t^i - \tilde{\mu}_i - F\xi_{t-1}^i\right)'\left(\xi_t^i - \tilde{\mu}_i - F\xi_{t-1}^i\right)\pi\,(\zeta) \tag{3.50}$$

[3] Moreover, Sims claims that this technique is useful when the data represent a historical break, like the end of a war.

[4] A very similar approach is proposed by Sims (2000).

If $|\zeta| < 1$, (3.50) becomes

$$Prob\left(\zeta|data\right) \propto e^{Nb(\zeta)} \left[\sum_i \left(\xi_t^i - \tilde{\mu}_i - F\xi_{t-1}^i\right)' H \left(\xi_t^i - \tilde{\mu}_i - F\xi_{t-1}^i\right)\right]^{-\frac{N(T-1)}{2}} \tag{3.51}$$

where $b\left(\zeta\right) = \frac{1}{T}\sum_{t=1}^{T-1}\frac{T-t}{t}\zeta^t$ and H is a TxT matrix that subtracts the mean from the errors.

3.6.2. Results from Numerical Simulations: A Tour with the Gibbs-sampler

Considering the data generated by the RBC model described in Section 3.3, I try to construct a structure similar to the Danish section of the *EU KLEMS* dataset. The parameters are generated using the data for the industries described in Table 3.3. The TFP growth data are generated as described by (3.2) without covariates while the errors are $NIID$ with a mean equal to zero and variance equal to 1.

Figure 3.2 contains four graphs. Each graph is constructed from the data generated from the RBC model using the same N and σ. T is changing and it is respectively equal to $1, 1,000, 5,000$, and $10,000$ observations.[5] This illustrates the marginal posterior density of ζ under a flat prior for $\{\tilde{\mu}_i\}$ and uniform priors for F, σ^2 and ζ on the horizontal axis, while on the vertical axis the initial values of TFPG ξ_0^i are represented. As it is possible to observe, the convergence for $\zeta|data$ is immediate, while the behavior of $\xi_0|\zeta$ is different considering more iterations.

Figure 3.3 represents the last graph of Figure 3.2 expressed as posterior density for ξ_0^i given ζ. The figure shows that the distribution is bell-shaped and concentrated on a negative value, while the dotted line represented the computation with the Malmquist Index procedure. Similar to the results obtained in Table 3.2, the graphs confirm that the Malmquist index procedure can provide a very precise value for the TFP growth, which are similar to the Gibbs-sampling distribution.

3.7. Empirical Application: Danish KLEMS Dataset

The data considered are collected by Statistics Denmark and by the *EU KLEMS* dataset. Table 3.3 displays the list of industries for which is possible to perform the analysis, according to the EU KLEMS industry classification, which is consistent with the International Standard Industrial Classification (ISIC) code. Moreover, the last column of the table shows which sectors are measurable, following the list suggested by Griliches (1994) and Nordhaus (2002).[6] The measurable industries are represented by the agriculture, forestry and fishing, mining, manufacturing, transportation and public utilities, wholesale trade and hotel and restaurant industries.

[5] In the simulation, the first observations are the same to stress the dependence of the arbitrary set of the initial condition.

[6] In this list, as suggested by Gordon (2000), I exclude retail because of the massive investment in ICT.

Figure 3.1.: Distribution of the initial TFP growths: Malmquist index procedure (upper part) and Gibbs-sampler (lower part)

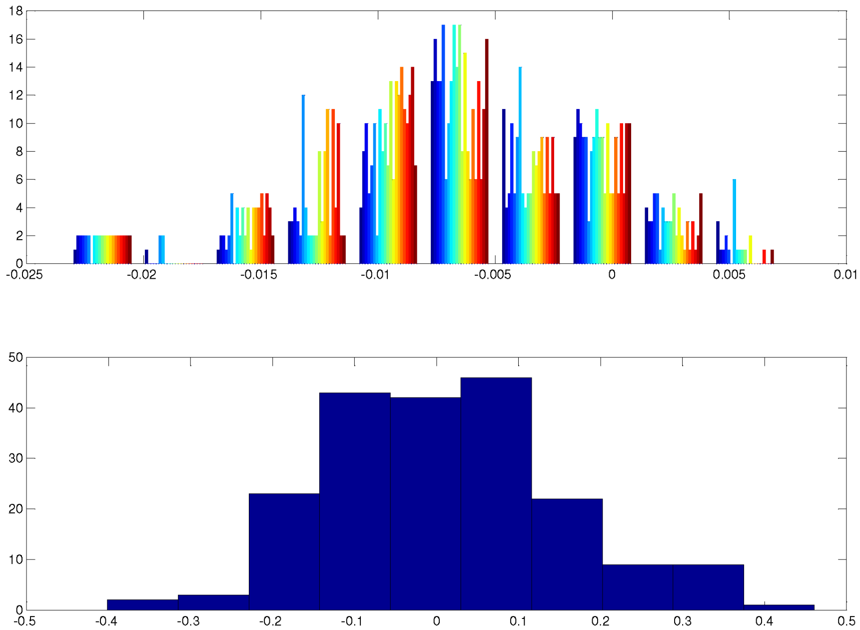


Table 3.2.: Horse race results. Root mean squared error (in %). Average of 10,000 simulations. (Standard error in parantheses.

TÖRNQVIST INDEX (BEA)	4.45 (0.22)
STATE SPACE MODEL	
ROSENBERG **INITIAL CONDITION**	4.48 (0.26)
GIBBS-SAMPLER **INITIAL CONDITION**	2.17 (0.43)
MALMQUIST INDEX **INITIAL CONDITION**	1.15 (0.32)

Figure 3.2.: Marginal posterior ζ and Gibbs-sampler

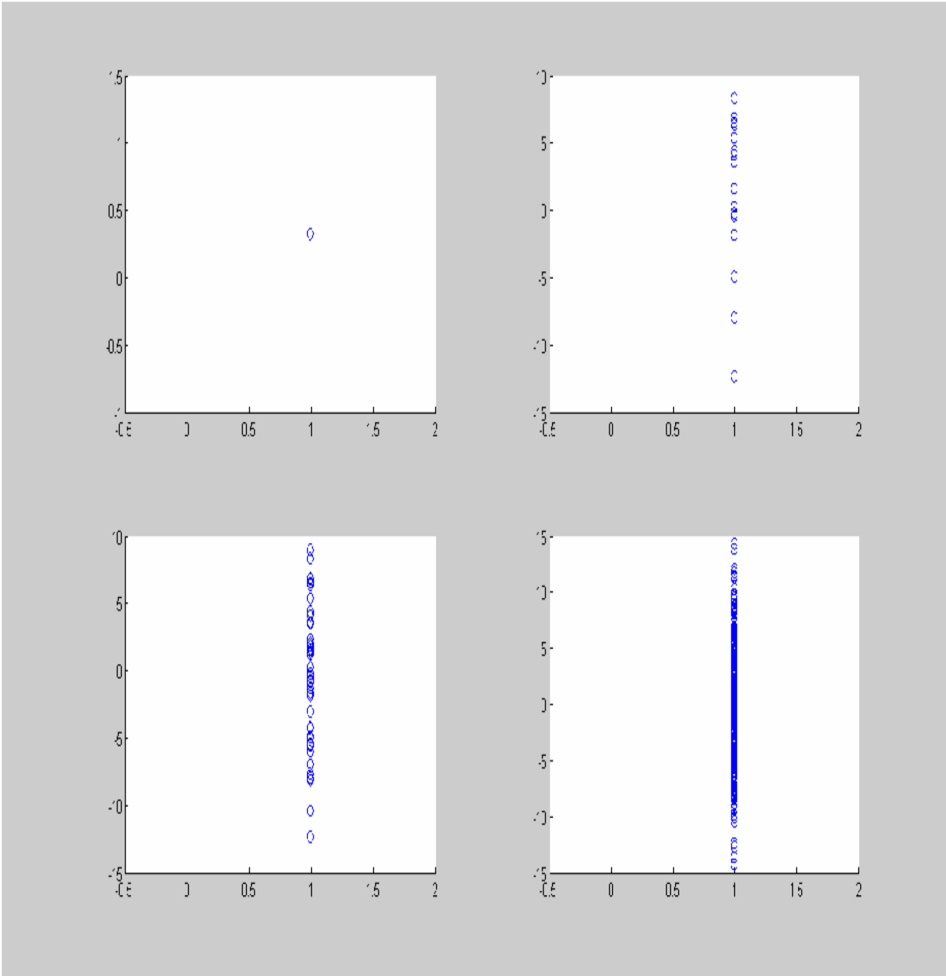


Figure 3.3.: Gibbs-sampler distribution and the Malmquist index procedure (yellow line)

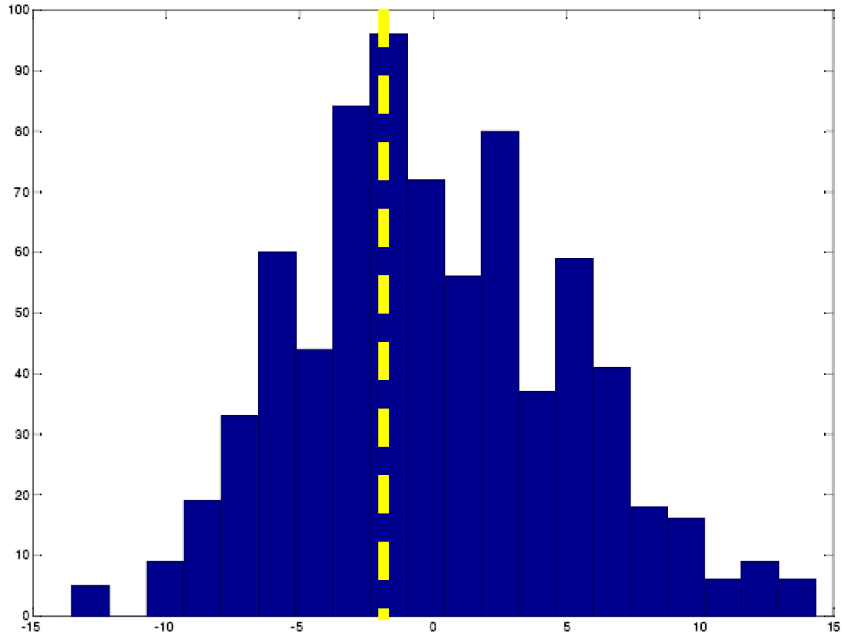


Table 3.3.: *EU KLEMS* Industries

DESCRIPTION	***EU KLEMS CODE***	Measurable Industry
TOTAL ECONOMY	TOT	
AGRICULTURE, HUNTING, FORESTRY AND FISHING	AtB	*
MINING AND QUARRYING	C	*
FOOD , BEVERAGES AND TOBACCO	15t16	
TEXTILES, TEXTILE , LEATHER AND FOOTWEAR	17t19	
WOOD AND OF WOOD AND CORK	20	
PULP, PAPER, PAPER , PRINTING AND PUBLISHING	21t22	
Chemicals and chemical	24	
Rubber and plastics	25	
OTHER NON-METALLIC MINERAL	26	
MACHINERY, NEC	29	*
ELECTRICAL AND OPTICAL EQUIPMENT	30t33	*
TRANSPORT EQUIPMENT	34t35	
ELECTRICITY, GAS AND WATER SUPPLY	E	*
CONSTRUCTION	F	
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	50	
Wholesale trade and commission trade, except of motor vehicles and motorcycles	51	*
Retail trade, except of motor vehicles and motorcycles; repair of household goods	52	
HOTELS AND RESTAURANTS	H	*
POST AND TELECOMMUNICATIONS	64	

* denotes measurable industries

Moreover, to obtain an initial condition given by (3.40), Table (3.4) shows the relationships among Danish industries. In the spirit of Caballero (2007) and Nunn (2007), I construct these relationships considering the intermediate input transactions in Denmark reported in the 1995 Danish input-output table.

Before implementing the methodology, it could be useful to test for the stationarity of the data.

3.7.1. Test for Unit Root

Looking at (3.11), one concern may arise about the stationarity of the data: not only the level of the time series but also the growth rate of the industry time series could display persistent effects of shocks and non-stationarity behavior. However, containing the *EU KLEMS* dataset time series with a maximum of 35 yearly observations per industry, it is quite difficult to detect non-stationarity with just one procedure. Therefore, a set of tests and checks should be performed.

At the first stage, it could be useful to plot the variable to check that some linear trends are present in the time series. Figure 3.4 contains three plots respectively for value added, investment and employment annual growth rate for the total economy. The figure shows no observable trend in data, which suggests that a linear trend should be considered in the test. Similar behavior can be observed for the industry time series.

The first tests I can perform are those introduced by Dickey and Fuller (1979) in the augmented version (ADF) and Phillips and Perron (1988) (PP). Given a time series X_t, the ADF considers the following AR(n) model:

$$\Delta X_t = \gamma_0 + \phi X_{t-1} - \sum_{j=1}^{n} \gamma_j \Delta X_{t-j} + \epsilon_t \tag{3.52}$$

and performs the test for a unit root is then carried out under the null hypothesis $\hat{\phi} = 0$ against the alternative hypothesis of $\phi < 0$. Alternatively, the PP test considers a reduced form of (3.52), which is the original Dickey-Fuller test, i.e.,

$$\Delta X_t = \gamma_0 + \phi X_{t-1} + \epsilon_t, \tag{3.53}$$

and test the parameter ϕ considering a non-parametric correction to the t-test statistic.

Table 3.5 provides the results for the ADF and PP tests without a trend and 2 lags for each sector and the total economy.[7] A first look at the Phillips Perron test rejects the null hypothesis of a unit root for all of the analyzed series. The null hypothesis is not rejected for some series (including all the time series for textiles and the output growth for agriculture).

[7] I also try to consider different values of the lags, especially, following Schwert (2002), $int\left[\frac{12T}{100}^{\frac{1}{4}}\right]$ with T number of observations. The results are always consistent.

Table 3.4.: Danish industries and relationship-specificity

Industry	**Most relationship-specific industry**
AGRICULTURE	FOOD
MINING AND QUARRYING	ELECTRICITY
FOOD , BEVERAGES AND TOBACCO	AGRICULTURE
TEXTILES, TEXTILE , LEATHER AND FOOTWEAR	TRANSPORT
WOOD AND OF WOOD AND CORK	ELECTRICITY
PULP, PAPER, PAPER , PRINTING AND PUBLISHING	WHOLESALE
Chemicals and chemical	AGRICULTURE
Rubber and plastics	AGRICULTURE
OTHER NON-METALLIC MINERAL	TRANSPORT
MACHINERY, NEC	TRANSPORT
ELECTRICAL AND OPTICAL EQUIPMENT	ELECTRICITY
TRANSPORT EQUIPMENT	ELECTRICTITY
ELECTRICITY, GAS AND WATER SUPPLY	ELECTRICITY
CONSTRUCTION	Wholesale
Sale	Wholesale
Wholesale	Retail
Retail trade	Wholesale
HOTELS AND RESTAURANTS	WHOLESALE
POST AND TELECOMMUNICATIONS	ELECTRICTY

Figure 3.4.: Value added, Investment and Employment Growth Rate. Total Economy.

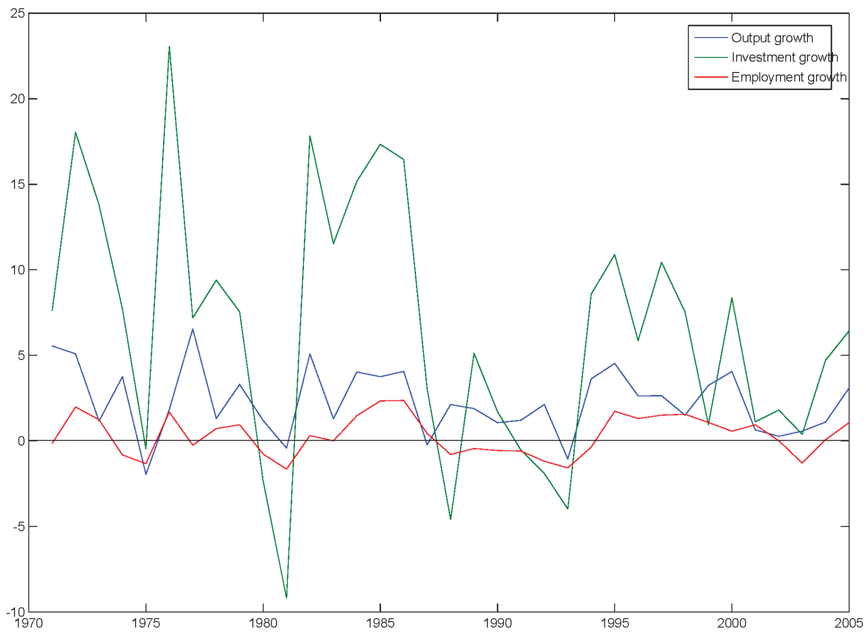


Table 3.5.: Results for the ADF and PP tests with no trend and with 2 lags.

Industry	Augmented Dickey Fuller			Phillips Perron		
Growth rate:	Output	Investment	Employment	Output	Investment	Employment
Total Industries	-3.663	-3.055	-3.014	-6.497	-24.762	-19.372
Agriculture and Fishing	-4.355***	-3.724	-2.829	-11.519	-24.408	-27.632
Mining and quarrying	-4.298***	-3.042	-4.451	-25.280	-31.521	-25.346
Food, Beverages and Tobacco	-2.002	-3.722	-3.332	-52.356	-42.534	-22.087
Te*tiles	-2.279**	-2.556***	-2.341***	-33.458	-41.840	-37.435
Wood	-3.364*	-5.634	-2.339***	-38.371	-36.795	-22.041
Paper and printing	-3.744	-2.952*	-3.198	-30.439	-41.947	-34.478
Coke	-2.572***	-3.574	-3.256	-39.219	-38.784	-38.323
Chemicals	-3.781	-3.185*	-3.947	-34.696	-43.279	-27.334
Rubber	-3.902	-4.011	-3.218	-27.657	-32.866	-18.079
Other non metal	-3.323	-3.445	-3.697*	-34.145	-30.225	-25.259
Basic metals	-3.736	-4.420	-4.490	-28.546	-24.216	-21.754
Machinery, NEC	-4.074	-3.024	-3.941	-31.890	-26.631	-28.774
Electrical and optical equip.	-3.242	-2.302*	-3.407*	-33.996	-37.974	-17.616
Transport Equipment	-3.564*	-3.789	-3.213*	-33.963	-32.891	-17.777
Recycling	-3.697*	-3.634*	-2.508***	-33.120	-40.336***	-16.261
Electricity, gas and water	-3.795	-2.559***	-3.233*	-42.089	-24.227***	-23.333
Construction	-3.502*	-4.054	-3.636	-30.599	-29.388	-22.102
Sale	-2.799**	-3.186	-2.580*	-33.675	-26.183	-25.160
Wholesale	-3.681*	-2.802	-2.272*	-33.981	-28.782	-34.893
Retail	-2.749*	-2.919*	-2.044*	-32.625	-35.148	-17.055
Hotels	-3.462*	-4.187	-3.396*	-34.116	-28.540	-19.733
Transport	-4.235	-3.675*	-0.529***	-32.519	-37.349	-24.296

***= significant at the 0.1% level.
**= significant at the 1% level.
***= significant at the 5% level.

Table 3.6.: Panel unit root analysis: IPS test.

Growth:	t-bar
Output	-3.455
Investment	-4.050
Employment	-3.331

IPS test assumes the null hypothesis of stationarity.
Critical values for rejection:
1%: -1.7550
5%: -1.810
10%: -1.930

However, in this case, the test for short time series has relatively low power. To be sure that the unit root does not affect the time series, we consider the test developed by Im et al. (2003) (IPS), which is useful for testing panel unit roots. The IPS test can be defined as a cross-sectional average of the ADF test for the individual sectoral equation. Table 3.6 shows that the hypothesis of non-stationarity can be strongly rejected.

I now apply the results obtained by the Kalman filter assuming that the initial condition is obtained by the Malmquist index procedure obtained from the procedures explained in Section 3.3 using both (3.32) and (3.40). I compare these results with the Solow-Törnqvist Index obtained from the EU KLEMS statistics (variable $VAconTFP$ of the dataset). These Solow residuals are computed as the difference between the growth rate of the value added and the growth rate of the inputs, while the factor shares are the two period average shares of the input in nominal value added assuming constant returns to scale. As an example of the procedure, Figure 3.6 shows a good approximation of the Malmquist index if it is compared with the results obtained by the Gibbs-sampler, while Figure 3.5 shows the differences between the Kalman filter and the Solow residual, respectively, and the initial condition.

Tables 3.7 and 3.8, considering respectively (3.39) and (3.40), display the comparison between these methodologies over the entire period, 1970-2005, and two sub-periods, 1985-1994 and 1995-2005. I consider 1995 as an important break year for the initiation of massive investment in ICT in the US (Stiroh (2002b)) and in Europe (Dahl et al. (2009)). Moreover, the upper part of these Tables represents the comparison for industries with a better-measured input.

Very similar patterns can be found in Table 3.8, where the coefficients of variation are almost identical (about 0.7). What is striking is that, while the Kalman Filter results are almost identical when comparing the two different Malmquist indexes used for the initial conditions, it is possible to find a difference for the less measurable industries. For example, the coefficients of variation of the Solow residual for the less measurable industries are 0.8 and 2.3 for the periods 1985-1994 and 1995-2004, respectively, while the same statics for the Kalman filter are lower (0.6 and 0.7, for the periods 1985-1994 and 1995-2004, respectively). These results suggest that capital could still be measured with some bias in the statistics especially for the less measurable industries. Moreover, this problem is accentuated after during the *New Economy* period.

Table 3.7.: TFP Measurement in Danish Industries: A Comparison (first table)

Industry	1970-2005		1985-1994		1995-2004	
	EU KLEMS	K.F.	EU KLEMS	K.F.	EU KLEMS	K.F.
Measurable industries						
Agriculture and Hunting	6.3	5.7	11.4	6.0	1.7	5.7
Mining	4.3	3.3	2.4	3.5	-2.2	3.3
Machinery	3.7	3.4	3.0	3.3	-0.1	3.6
Manufacturing NEC	0.1	0.1	2.0	0.0	-1.0	0.1
Electricity, Gas and Water	1.3	0.9	-2.7	1.0	0.0	1.0
Wholesale	1.6	1.9	2.9	1.8	1.8	1.8
Hotels and Restaurants	-1.6	-1.5	-5.0	-1.6	-3.2	-1.6
Less measurable industries						
Food, Beverages and Tobacco	1.8	2.4	0.4	2.8	-1.6	1.9
Textiles	2.4	1.3	-1.8	1.5	-0.2	1.3
Wood	0.7	0.5	-4.9	0.4	-0.7	0.9
Pulp, Printing and Publishing	0.6	0.2	-5.6	0.3	0.3	0.3
Chemicals	4.8	3.2	5.9	3.1	1.8	2.9
Rubber and Plastics	1.9	1.6	-3.2	1.5	-1.4	1.6
Other Minerals	0.5	0.5	0.2	0.3	-1.9	0.6
Transport Equipment	0.7	0.2	2.1	-0.1	-1.9	0.9
Sale Motor Veichles	-0.1	0.1	3.2	-0.2	-0.8	0.0
Retail	0.5	0.6	2.9	0.6	-0.2	0.8
Post and TLC	1.8	1.9	5.8	2.1	3.5	1.7

EU KLEMS denotes Solow residual

K.F. denotes the TFP growth estimated from the State-space model

Table 3.8.: TFP Measurement in Danish industries: A Comparison (second table)

Industry	1970-2005		1985-1994		1995-2004	
	EU KLEMS	K.F.	EU KLEMS	K.F.	EU KLEMS	K.F.
Measurable industries						
Agriculture and Hunting	6.3	6.0	11.4	5.9	1.7	6.2
Mining	4.3	3.4	2.4	3.3	-2.2	3.5
Machinery	3.7	3.4	3.0	3.3	-0.1	3.5
Manufacturing NEC	0.1	0.0	2.0	0.1	-1.0	-0.1
Electricity, Gas and Water	1.3	0.9	-2.7	0.8	0.0	1.0
Food, Beverages and Tobacco	1.8	2.3	0.4	2.3	-1.6	2.3
Wholesale	1.6	1.9	2.9	2.1	1.8	1.5
Hotels and Restaurants	-1.6	-1.4	-5.0	-1.5	-3.2	-1.2
Less measurable industries						
Textiles	2.4	1.5	-1.8	1.5	-0.2	1.4
Wood	0.7	0.5	-4.9	0.4	-0.7	0.5
Pulp, Printing and Publishing	0.6	0.1	-5.6	-0.1	0.3	0.3
Chemicals	4.8	3.5	5.9	3.5	1.8	3.5
Rubber and Plastics	1.9	1.3	-3.2	1.3	-1.4	1.2
Other Minerals	0.5	0.3	0.2	0.3	-1.9	0.2
Transport Equipment	0.7	-0.2	2.1	-0.3	-1.9	-0.1
Sale Motor Veichles	-0.1	-0.1	3.2	-0.0	-0.8	-0.2
Retail	0.5	0.5	2.9	0.3	-0.2	0.9
Post and TLC	1.8	1.6	5.8	1.6	3.5	1.5

EU KLEMS denotes Solow residual

K.F. denotes the TFP growth estimated from the State-space model

Finally, in Figure 3.6 the Törnqvist Index (green line) is compared to the Kalman Filter estimation (blue line).

3.8. Conclusion

Different econometric techniques of estimation and computation of technological change have been analyzed in the literature; however, when inputs, especially capital, are affected by measurement errors, the results may be biased. In this chapter, I propose a new methodology based on the State-space model and adopting Kalman Filter techniques, through which it is possible to estimate TFP growth without considering investment series instead of capital. I also analyze the problem for the initial condition of TFP growth. I compare four different approaches: the Solow residual, the Maximum Likelihood estimation, the Gibbs-sampler and the Malmquist Index. Comparing the results using the Gibbs-sampler, it is possible for the root mean squared of this procedure to be two-thirds lower than the Solow residual when capital contains measurement error. In addition, I extend this framework to panel data. The empirical application utilizes Danish industry data. The comparison between the TFP growth measures provided by the Danish national statistics and the Kalman filter estimations suggests that capital can play an important in estimating technological change, especially for industries where it is more difficult to measure the inputs precisely.

Figure 3.5.: Initial value for the Danish industry: Malmquist index procedure and Gibbs-Sampler

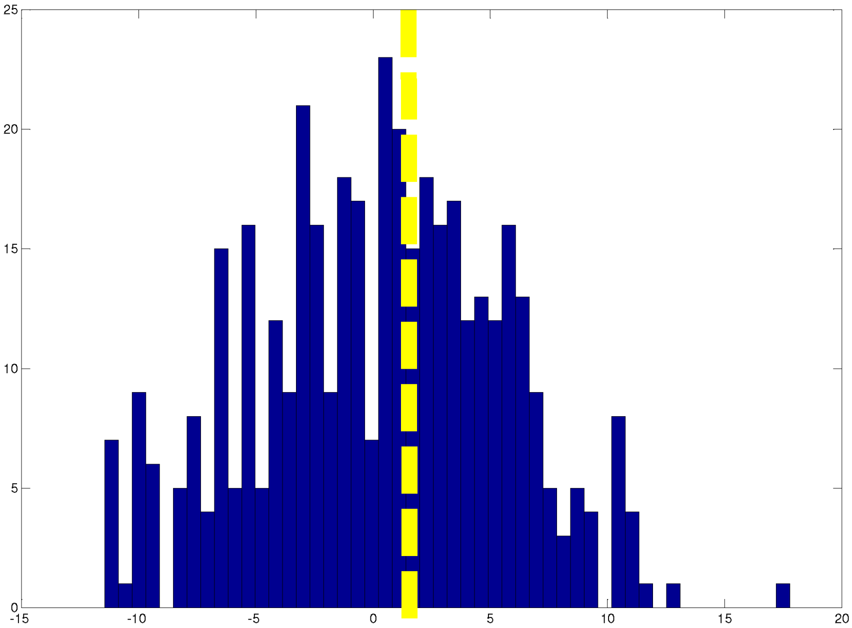
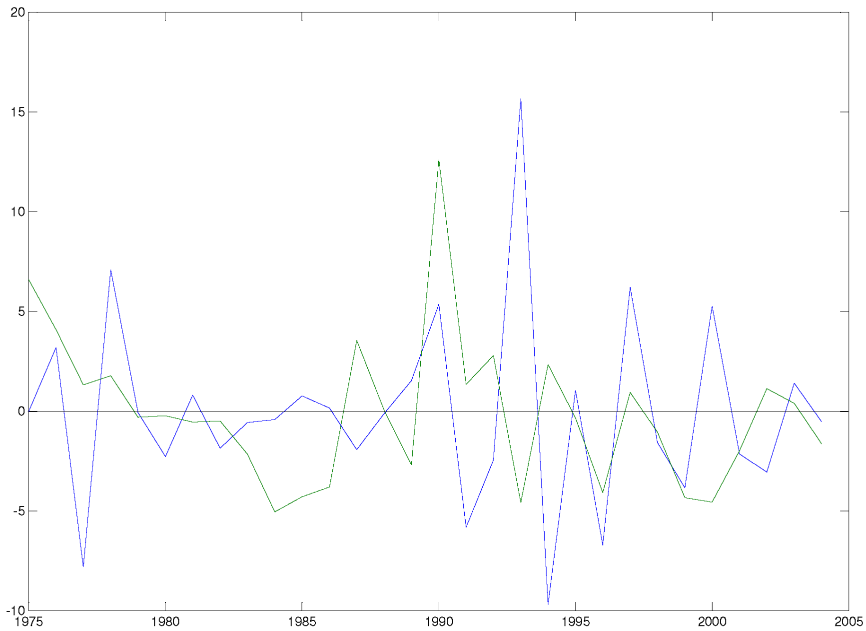


Figure 3.6.: Danish retail: Törnqvist index and Kalman filter estimation



4. Is ICT a Jack-in-the-Box? A Counterfactual Approach for Identifying TFP Spillovers.

Recent empirical evidence suggests that investments in information and communication technology (ICT) are a strong determinant in enhancing total factor productivity (TFP). This chapter proposes a new approach for identifying spillovers that emanate from new technologies on productivity combining a counterfactual decomposition derived from the main Malmquist index properties and modifying the econometric technique introduced by Machado and Mata (2005). A new definition of technological space based on firms' propensity to invest both in communication and in innovative processes is also considered. Applying this methodology to a dataset of Italian manufacturing firms, I find that externalities are relevant for TFP growth once the definition of technological space is based on network activities and that the most productive firms are also the primary recipients of ICT spillovers.

4.1. Introduction

A considerable number of macroeconomic models identify spillovers as one of the major sources of growth. The underlying assumption is that firms, independently of the investment rate in productive capital, can upgrade freely their own technological level with the knowledge developed in their local neighborhood. This theoretical framework has deep roots in economics and has produced a vast amount of literature, including, among others, Marshall (1890), Schumpeter (1934), Arrow (1962), and, more recently, Romer (1986), Glaeser et al. (1992) and Acemoglu et al. (2006). These studies analyze the effects of knowledge spillovers for firms clustered in the same geographical area and how ideas can be imitated, observed or just disseminated through the trade or transfer of skilled workers.

This chapter proposes a new approach for identifying and estimating the presence of ICT spillovers based on a certain level of TFP growth. The main reason for introducing a new approach to estimate these externalities are the contradicting results in the current literature. First of all, even if empirical studies on knowledge externalities concentrated primarily on the effects of research and development (R&D) spillovers (Bernstein and Nadiri (1988)), recent analyses focus on the effects produced by investments in information and communication technology (ICT),[1] which are considered important sources of total factor productivity (TFP). The importance of ICT on TFP growth exists for three reasons. First, ICT investments can increase the level of TFP,

[1]OECD (2002) defines ICT as two different types of tangible (*Computing* and *Communication Equipment*) and one type of intangible asset (*Software*).

thereby decreasing transaction costs related to the communications and the matching of supply and demand.[2] Second, new technologies can improve the logistic-intensive services by reducing transportation costs and increasing trade between different areas (Hubbard (2000)). Finally, the intensive use of new communication goods can improve efficiency in sharing and processing information knowledge in the production process by disseminating ideas freely or at a low cost, thus extending the benefits of the market for all workers and consumers (Jones and Romer (2009)). Moreover, several studies support the hypothesis that ICT is the principal reason for growth differences between the US (which is characterized by simultaneous investment increases in new technologies and large TFP gains) and most Continental European countries (characterized by less intensive ICT capital and productivity slowdown) (Jorgenson et al. (2005) and van Ark et al. (2008)).

In addition, while the growth-accounting framework introduced by Solow (1957) can only confirm a positive and strong relationship between between investment in new technologies and growth[3] (the so-called *Solovian growth*), verifying the existence and quantifying the impact of ICT spillovers on the economy (*Schumpeterian growth*) represents an important challenge from a theoretical and empirical point of view, especially when a comparison is made between macro and micro level data. On one hand, Hall (1988), Basu and Fernald (1997), Stiroh (2002a) and Diewert and Fox (2008) support the hypothesis that production functions in the US exhibit increasing returns to scale, which are usually confused with spillover effects, Bartelsman (1995) suggests that externalities observed in the American data are no more than measurement errors, Bartelsman and Hinloopen (2004) claim that in Europe possible spillovers are washed out by the restrictive product and labor market regulations and institutions. On the other hand, once an empirical analysis is conducted on firm level data, ICT investments seem to greatly improve productivity and the internal organization of the production units (Bresnahan et al. (2002) and Black and Lynch (2004)).

A possible reason for this lack of consensus is that ICT spillovers are usually analyzed with the same framework that is used for R&D. Even if both R&D and ICT capital are mostly intangible, ICT can be part of the investment decisions of nearly all firms, such that new quantitative issues can arise. First, the traditional econometric models usually do not account for the entire heterogeneity of the productive process. In addition, once firm-level data is taken into consideration, it is difficult to identify whether increased productivity is caused by the externalities of ideas or peer effects. For example, the number of production units invested in ICT is influenced by the average action of neighborhood firms. Another important point is that the definition of an area in which spillovers can also have an effect. Identifying a certain spatially-interconnected region as a technological space may be misleading since the introduction of new communications systems creates the possibility of new forms of long-distance networks.

[2] Jensen (2007) is an original case study that evaluates the importance of the introduction of mobile phones to positive market performance in the Indian fisheries industry.

[3] Jorgenson and Vu (2005) analyze the importance of ICT capital deepening for the world economy. Concerning the limitation of the growth accounting, van der Wiel and van Leeuwen (2003) compare Solow residuals and production function estimations for Dutch data finding relevant deviations controlling for competition, innovation and economies of scale. They argue that part of these differences could be attributed to ICT spillovers.

This chapter proceeds in three different steps. First, I illustrate a counterfactual exercise examining the characteristics of the Malmquist index based on assumptions that the economy has respectively constant returns to scale (CRS) and variable returns to scale (VRS). Second, I combine these properties with the technique introduced by Machado and Mata (2005) based on a quantile regression (QR) approach , which has been used primarily in labor economics to study wage differentials. Third, by exploiting the decline in costs of communication, ICT investment is divided into an information and technology (IT) part (usually relevant for the production processes) and a communication (C) part (used to interconnect firms over long distances). Finally, the empirical exercise is based on a dataset of Italian manufacturing firms (the *Uni Credit Group* dataset) during the period 1998-2003.

Italy represents a valuable case study because of the micro and macro levels of ICT investment and the geographical configuration of the country. Although, van Ark et al. (2008) define Italy as a country with scarce ICT investments and Daveri and Jona-Lasinio (2005) document a scarce number of ICT producers and low labor productivity considering industry-level data from the *EU KLEMS* dataset, several micro-level studies show that firms investing substantially in ICT seems are very productive (Matteucci et al. (2005)). This guarantees a certain level of heterogeneity in the data. Milana and Zeli (2002), implementing data envelopment analysis (DEA) and stochastic frontier analysis methods, find that ICT also enhances efficiency and capacity utilization. This evidence is also supported by Fabiani et al. (2005), who show that ICT is an important opportunity for firms' growth, even if the prevalence of small firms, low level of human capital and Italian labor market regulations present relevant obstacles to the diffusion of ICT.[4] Moreover, another interesting aspect is represented by the different orographic conditions and different historical institutions that have existed in Italy since the Middle Ages (Altan (1986)). The Italian economy is represented by the unique presence of the so-called *distretti*, which are small district-like areas characterized by very similar firms (Beccattini (1998)). As Porter (1990) remarks in his study of the Italian ceramics and gold jewelry districts, these homogeneous areas could enhance the rapid adoption of innovation and stimulation of growth throughout knowledge spillovers. Another important value of the dataset is the exploration of geographical within-country variation, which can control for country institutional effects. This characteristics may be useful for defining an appropriate technological space and to study the effect of investments in communications that create new networks. In the Italian case, results are sensitive to assumptions about technological space. If the traditional definition of geographical space is assumed, results suggest that TFP growth is entirely driven by pure technological change. On the other hand, once the effect of communication is taken into account, spillovers can contribute to half of total productivity changes and the most productive firms are also the foremost recipient of ICT spillovers. This situation suggests that not only ICT producers, but also all the users of new technologies can benefit of a new source of growth. Furthermore, a policy implication is that IT goes hand in hand with

[4] Differently from other European countries, the Italian economy was not very involved in the globalization process: Daveri and Jona-Lasinio (2008) estimate that about 35% of the total nonenergy inputs was imported by the average manufacturing industry in Italy. An additional investigation on the Italian Input-Output tables shows that this shares declines to 6-8% for technlogical intermediates. Statistics are available from the author.

communication in augmenting TFP.

The rest of this chapter is structured as follows. Section 2 illustrates the main differences between ICT and R&D investments and provides definitions for spillovers and the technological space. Section 3 discusses the role played by the counterfactuals in the Malmquist index to explain spillover effects. Section 4 introduces the econometric specification considered in the empirical part. Section 5 illustrates the econometrical issues and provides a QR analysis, the Machado and Mata (2005) technique and the definition of new networks based on bivariate probit regressions. Section 6 introduces the dataset on Italian Manufacturing firms. Section 7 discusses the results, and Section 8 concludes.

4.2. The Peculiarity of ICT Investments

Both *New Growth Theory* models and econometric specifications identify ICT spillovers by using the traditional framework adopted for modeling R&D spillovers. However, several arguments suggest that new technologies should be treated differently from traditional R&D investments. One radical difference between these two types of assets is that R&D externalities are completely represented by *knowledge* spillovers (such as, ideas borrowed by other firms) while ICT investments can also create the so called *rent* spillover effects (such as, measurement errors in price indexes due to intensive decreases in ICT prices and by intangible nature of most new technological goods) (Griliches (1992)).[5] These are not proper characteristics of R&D investments, which are part of the decision of the most technologically advanced firms and are also complementary to high skill-educated labor, while the behavior of ICT prices is a new phenomenon, which has nonetheless increased the number of potential adopters.

A second relevant peculiarity of ICT is the possibility of generating spillovers in an unlimited geographical space. While the literature on R&D externalities assumes that firms usually receive benefits through geographical closeness, where the sum of the total stock of patents or aggregate investments in R&D in an area are the measures of spillovers, modern communication systems permit long distance transmission of technologies and thus creates possible network externalities (van Ark (2002) and Oulton (2002)), enhancing both the propagation of ideas and the number of users.

Appendix F illustrates a model of spillover effects introduced by Bloom et al. (2007) and contains a modification for ICT. By exploring the main results of the two-stage game of their model and following Glaeser and Scheinkman (2000) and Guiso and Schivardi (2007), I am able to identify two different types of their spillover effects.[6] The first class is represented by the so called *real spillovers*. Equation (F.6) in Appendix F summarizes this concept. Defining V_0 as the quantity of productivity or value added of firm 0 and

[5] Jorgenson et al. (2005) analyze the effects of ICT prices on TFP growth.

[6] In the literature it is also possible to find a third type of externality: *information* spillovers, where the effects do not influence the profits or the stock of knowledge, but the information of the shift of the probability distribution of the production function, $E\left[\phi\left(ICT_0, ICT_j\right)\right] = \int A d\Psi\left(TFP|ICT_j\right) f\left(ICT_j\right) = E\left(TFP|ICT_j\right) f\left(ICT_0\right)$ with the cumulative density function $\Phi\left(TFP|ICT_j\right)$.

ICT_0 and ICT_j as the amount of ICT investment respectively for firms 0 and j, in presence of spillovers it is possible to obtain the following positive cross derivative:

$$\frac{\partial^2 V_0}{\partial ICT_0 \partial ICT_j} > 0.$$

In a defined space the ICT factor demand of production unit 0 is positively influenced by the level investment of other firms. This type of spillover is similar to those described in the literature as those increasing network externalities where the utility from adoption is positively correlated with total number of users (Katz and Shapiro (1986)). This spillover is also described as a search spillovers, where the benefit of searching increases with the number of other searchers (Diamond (1982)), or the intermediate input variety, where the higher variety of intermediate inputs increases productivity (Romer (1986)).

The second type of externality is represented by *knowledge spillovers*. Unlike the previous case, firms' productivity does not depend on the level of investment but rather on the amount of ideas. Agents learn how to increase their own productivity from neighbors in the technological space. In this case, I can disembody the positive productivity term of the production function ϕ, which, as in (F.7), is defined as ICT_0 with a fraction κ coming from the ideas of other firms in technological space $SPACE - 0$:

$$\phi\left(ICT_0, \overline{ICT}_{SPACE-0}\right) = \left(\overline{ICT}_{SPACE-0}\right) \phi\left(ICT_0\right).$$

The presence of positive spillovers gives $\frac{\partial ICTTFP_0\left(\kappa \overline{ICT}_{SPACE-0}\right)}{\partial\left(\kappa \overline{ICT}_{SPACE-0}\right)} > 0$

The model shows that the area in which firms do compete in creating new products also provides firms with ideas from competitors and increases a firm's productivity by using new technological goods for ICT. For these reasons, the usual measure for R&D, which is often defined as simple geographic neighborhood, is no longer a good fit. In addition, from an industrial organization point of view, investment in R&D can be modeled as a competitive tournament, where the "winner" (i.e., the firm owning a particular patent) takes all the benefit. In the case of ICT, the tournament is not competitive since the use of a certain ICT does not preclude other users from benefiting. For these reasons, this chapter focuses solely on knowledge spillovers.

4.3. Counterfactuals and the Malmquist index

In many scholars' opinions, ICT investments are defined as a general-purpose technology because they can sensibly modify the structure of a production function and thus represent a radical change in economic growth. This is comparable to the presence of steam engines during the Industrial Revolution (Crafts (2002)), or the introduction of electricity in firms during the first years of the 20^{th} century (Jalava and Pohjola (2008)).

A representation of these stylized facts in which ICT technologies can change the technological frontier is displayed in the upper part of Figure 1, which follows a modified version of the framework proposed by Bartelsman and Hinloopen (2000). This setup illustrates the potential output growth during the periods $t = 0$ and $t = 1$ for a unit of production $Y = F\left(K^{ICT}, K^{NICT}, N\right)$, which is a function of the amount of ICT and non-ICT capital invested, K^{ICT} and K^{NICT}, and the labor employed, N. The representation is in a bi-dimensional input-output space (y, ict), where output and ICT are normalized by other inputs of production, such as $y = \frac{Y}{K^{NICT}N}$ and $ict = \frac{K^{ICT}}{K^{NICT}N}$,[7] and the presence of three different technological frontiers, one, T_0 for $t = 0$ and two possible technologies at time $t = 1$, T_1 and T_1^*. T_0 and T_1^* are technological frontiers under CRS so they are represented without kinks. Moreover, all factors are used under full efficiency, while global constant return to scale are assumed only during the first period.

The observable total growth path between $t = 0$ and $t = 1$, displayed by the segment $y_1^1 - y_0^0 = \overline{A_1C}$, can be decomposed into three different factors. The first channel, also known as *Solovian growth*, is represented by a capital deepening effect. By increasing the investment level by $\overline{ict_1 ict_0}$ in this economy, the production is enhanced by the quantity $\overline{A_1E}$. The second effect, named as *Schumpeterian growth*, is represented by the shift in productivity represented by change in the technological frontier under CRS from T_0 to T_1^*, i.e. the distance $\overline{ED}$. If there were no externality effects, the production technology would be T_1^*. However, given some diffusion of ideas and their implementation in the production process, a third effect, caused by the spillover, can shift the technological frontier from T_1^* to T_1 obtaining a higher level of TFP (represented by $\overline{CD}$). In other words, the economy can obtain a "free lunch" that does not depend on capital accumulation or expected technological change.

As displayed in the lower part of Figure 1, the same framework can be represented for some techniques derived from DEA. Some properties derived from the Malmquist index under CRS and VRS[8] can be useful for computing a measure of the effects of externalities. In particular, besides the three technologies represented in the upper part of Figure 1, two new technological frontiers can produce the output $C\left(y_1^1, ict_1\right)$ during the period $t = 1$ can be represented by T^2 and T^{2*}, which are the VRS and CRS production frontiers, respectively. Even if the final output is identical, the two corresponding counterfactuals, B_1 and B_2 (i.e., the amount of output which would have been produced with the technologies of the second period if the quantity of input had been the same under CRS and VRS) differ. These two points can be useful to define minimum and maximum levels of spillover effect. The distances $\overline{ict_0 B}$ (which is equal to the difference $\overline{Cict_1} - \overline{B_2 ict_2}$) and $\overline{ict_0 B^1}$ (equal to $\overline{Cict_1} - \overline{B_2 ict_0}$) can respectively provide the lower and upper bounds of spillover effects $\overline{CD}$.[9]

[7] In this case an increase of ICT corresponds an increase of output over time. This assumption is also confirmed by the data.

[8] For the applications of the Malmquist index to productivity estimation problems under CRS, see Färe et al. (1989); for an application under VRS, see Ray and Desli (1997) and Färe et al. (1997).

[9] These counterfactuals are usually computed throughout DEA methods. The scale distance $\overline{B_2D_2}$ considering the formal formula as in Lovell (2003): $\overline{B_2D_2} = S\Delta^t\left(ict^t, y^t, ict^{t+1}, y^{t+1},\right) = \frac{D_o^t\left[ict^t, y^{t+1}/D_o^t\left(ict^{t+1}, y^{t+1}\right)\right]}{D_i^1\left[y^t, ict^{t+1}/D_i^i(y^t, ICT^t)\right]} = \frac{f^t\left(ict^{t+1}\right)/f^t\left(ict^t\right)}{ict^{t+1}/ict^t}$ where D_o and D_i are respectively the output and input distance functions, as described in Section 1.6.

Since there is no *a priori* reason to prefer one of the two types of technologies, distance $\overline{CD}$ can be approximated as an unweighted average of the two segments $\overline{D^1C}$ and $\overline{D^2C}$. Given a certain amount of ICT, this average is the difference between effective output at time 1 with technology T_1 and the output which would have been produced if technology had been free of spillover effects. This definition of the counterfactual will provide important information for implementing the QR procedure, which will be described in Section 5.

4.4. The Econometric Specification

Given the stylized facts illustrated in Section 3 and the main results obtained from the model in Appendix F, the econometric analysis should not only take into account the problems concerning basic empirical equation and the choice of variables for specification and econometric techniques, but should also account for issues of self-selection. In addition, I apply a new definition of technological space, recognizing the possibility that firms can have networks outside the geographical area.

Concerning the basic empirical equation, I follow the framework for studying externalities suggested by Guiso and Schivardi (2007):

$$TFPG_i\left(t\right) = \alpha_0 + \alpha_i + \beta_0 \epsilon_i\left(t\right) + \beta_1 \epsilon\left(t\right) + \beta_2 \overline{TFPG}_{S\ TECH}\left(t\right) + u_i\left(t\right) \tag{4.1}$$

where $TFPG_i\left(t\right)$ is the yearly percentage change of the firms' performance, α_0 is a constant, α_i is a set of firm dummies controlling the long-run efficiency of the unit of production, $\epsilon_i\left(t\right)$ and $\epsilon\left(t\right)$ are the firms' idiosyncratic and common shock, respectively, and $\overline{TFPG}_{S\ TECH}\left(t\right)$ is the percentage performance of the technological space $S\ TECH$ and $u_i\left(t\right)$, which is the error term uncorrelated with the two shocks. With an appropriate estimation, a positive and significant $\hat{\beta}_2$ provides the presence of spillovers in the technological space.

In this specification several variables related to firms' performance may be considered, such as, employment, value added and labor productivity. In this case, I focus my attention on TFP growth: since ICT is assumed to be a general-purpose technology, which has been adopted pervasively in most sectors, the first effects are more visible in efficiency than in the reallocation of labor (Aghion and Howitt (1992)). Similar to the input-output space (y, ict), represented in Section 3 and the results given by Appendix F, I define $TFPG_i\left(t\right)$ and $\overline{TFPG}_{S\ TECH}\left(t\right)$ as TFP growth, which is estimated by using the Levinsohn and Petrin (2003) methodology.[10] For the variable related to the percentage adjustment of other firms' technological change, TFP growth of the most productive firm in terms of level is chosen[11] in the technological space, since only the mostproductive firms can have positive spillovers (Acemoglu et al. (2006)). Similar to the procedure suggested by Jorgenson et al. (2005), ICT firms are considered the ICT

[10] Using simulated panel firm level data, Van Biesebroeck (2006) shows that this type of technique provide very accurate estimations. A detailed explanation of this procedure is provided in Appendix G.

[11] In the empirical part, regressions with the most productive ICT firms in terms of growth have been considered providing similar results. Output available upon request.

users and the producers. A list of these types of industries is represented in Table 4 in Appendix H. Common and individual shocks are estimated from

$$\Delta\psi_{i,S\ TECH,t} = \beta Z_{i,S\ TECH,t} + \xi_{j,t} \tag{4.2}$$

with $\psi_{i,S\ TECH,t} = \frac{\Delta y - \Delta\overline{y}}{\sigma_y}$, where y and $\overline{y}$ are the value added and its average, respectively, σ is the standard deviation and Z is a set of year and industry dummies (also interacted with the geographical variables), such that $\epsilon_{i,S\ TECH,t} = \Delta\hat{\psi}_{i,S\ TECH,t}$, while the idiosyncratic shocks are considered as the residuals of the regressions, $\hat{\xi}_{j,t}$.

Once the variables are chosen for (4.1), three challenging identification problems arise. First, empirical evidence shows that firms with spillovers characteristics tend to be located near each other (Glaeser et al. (1992)). This problem is relevant when cross section data is considered. In this case, the econometrician would not be able to realize whether the increase in productivity is given by the network effects or by the unobserved lower adoption in that location. The second problem is the so-called *reflection problem* introduced by Manski (1993). Firms in the same group tend to behave similarly. Usually, these types of problems cannot be easily solved because it is difficult to disentangle the effects generated by pure spillover effects from those related to this bandwagon effect. Finally, it would be difficult to disentangle the effects emanating from common unobservable shocks, which could be confused with technological spillover effects. However, as discussed in the following sections, the particular structure and the characteristics of the data allows these two effects to be separated.

4.4.1. Identifying the Technological Space

To identify a new technological space, which may be different from the geographical location of the neighborhood, a multivariate approach is used that decomposes the information related to each firm's decisions to invest in capital directed to improve the production process, and the goods enhancing the probability of exchanging or sharing ideas. In other words, it is expected that the decision to invest in both IT and C can be relevant for being part of a network that is different only with regard to the neighborhood.

Following Greene (2008a), I implement a bivariate probit model estimated with a full information maximum likelihood procedure (FIML). This procedure, which is similar to the seemingly unrelated regression, involves the simultaneous estimation of two probit equations:

$$\begin{cases} IT^* = \delta_1 X_1 + \epsilon_1 \ with\ IT = 1\ if\ IT^* > 0, 0\ otherwise \\ C^* = \delta_2 X_2 + \epsilon_2\ with\ C = 1\ if\ C^* > 0, 0\ otherwise \end{cases} \tag{4.3}$$

where IT^* and C^* are the investment in IT and C, respectively, and the errors ϵ_1 and ϵ_2 are joint normally distributed with average $E[\epsilon_1|X_1, X_2] = E[\epsilon_2|X_1, X_2] = 0$, variance $Var[\epsilon_1|X_1, X_2] = E[\epsilon_2|X_1, X_2] = 1$ and covariance $Cov[\epsilon_1, \epsilon_2|X_1, X_2] = \rho$ such that the model (4.3) collapses to two separate probit models for IT and C if $\rho = 0$. A strong propensity to invest in IT and C, as, for example, a value higher than the median, can be associated with a new networking area in which the most technological investments belong.

The set of regressors X_1 and X_2 can have common variables, such as information from the balance accounting variables (as value added or the financial leverage), geographical location, or the type of industry. On the other hand, other variables related to the network activities of the firms, such as outsourcing, participation in a trade consortium or production or R&D joint ventures, can be useful in explaining the probability of investing in communication goods. The definition of this new type of technological space helps explain problems related to the peer effect, since firms can also increase their productivity from ideas coming from outside their own geographical area.

4.5. The Need for Quantile Regressions Analysis

In most empirical studies, productivity is studied using Ordinary Least Squares (OLS) or Instrumental Variable (IV) regression techniques. However, these methodologies may not be able to provide a complete analysis on the entire heterogeneity of the productivity process, which is more prominent when the dataset is characterized by different industrial clusters. The Quantile Regression (QR) analysis, introduced by Koenker and Bassett (1978), represents one of the best strategies to address this problem for four reasons. First, the theoretical frameworks suggest the presence of a multimodal distribution of TFP growth (Quah (1996) and Basu and Weil (1998)). This is supported by empirical evidence at the micro (Bartelsman and Doms (2000)) and macro (Kumar and Russell (2002)) level. Second, QR estimators can be more efficient than OLS when the error terms are not log normally distributed. Third, the QR estimator is less affected by outliers than the OLS. Finally, QR shows robust results and does not require the existence of a conditional mean for consistency.

More formally, QR considers $Q_\theta\left(TFPG|X\right)$ with $\theta \in (0,1)$ and the θ^{th} quantile of the distribution of the TFP growth given the vector x of covariates in (4.1). The QR model for TFP by industry and by year is given by the following form:

$$Q_\theta^t\left(TFPG|x\right) = x^{'}\beta_t\left(\theta\right) \tag{4.4}$$

where x is a $k\times 1$ vector of covariates and $\beta_t\left(\theta\right)$ is a conformable vector of QR coefficients, which is describe in Section 6. $\beta\left(\tau\right)$ can be estimated by minimizing β

$$\tfrac{1}{n}\textstyle\sum_{i=1}^{n}\gamma_\theta\left(TFPG_i - x_i^{'}\beta\right)$$

with

$$\gamma_\theta = \begin{cases} \theta u & for\ u \geq 0 \\ \left(\theta-1\right)u & for\ u < 0 \end{cases} \tag{4.5}$$

This allows me to study and interpret specific parts of spillovers effects for different points of the productivity distribution and in implementing a modified version of the Machado and Mata (2005) technique.

4.5.1. The Machado and Mata Technique

Machado and Mata (2005) propose an estimator that combines quantile regression and bootstrapping for generating counterfactual densities. This technique, which is similar to an extended Oaxaca-Blinder decomposition (Oaxaca (1973)), is widely used in labor economics to study wage discrimination (Autor et al. (2005), Albrecht et al. (2003, 2006), Melly (2006) and Burda et al. (2008)) and disentangles the observed TFP into *price* (components estimated from the matrix of prices $\hat{\beta}_\tau(\theta)$) and *quantity* components (i.e., to the distribution of the x components). This can be translated into three channels: a capital accumulation, a technological change and a spillover channel. In detail, the procedure can be summed up in five different steps:

1. A random sample of size m is generated from a uniform distribution
$$u \in \sim U[0,1] : u_1, \ldots, u_m$$
2. For each dataset $Z(t)$ at time t and each $\{u_i\}$ $Q_{u_i}(TFPG|z;t)$ is estimated yielding m estimates of the QR coefficients $\hat{\beta}^t(u_i)$.
3. A random sample of size m is generated with replacement from the rows
$$\{z_i^*(t)\}, i = 1, \ldots, m. \text{ of } Z(t).$$
4. A random sample of size m from the desired distribution is constructed
$$\left\{TFPG_i^*(t) \equiv z_i^*(t)' \hat{\beta}^t(u_i)\right\}_{i=1}^m.$$
5. The class $C_1(1)$ of $TFPG$ is considered and generated by other industries of the space technology and, given $I_1 = \{i = 1, \ldots, m | y_i(1) \in C_1(1)\}$, the subset of random sample is then generated in Step 1, corresponding to I_1, i.e., $\{TFPG_i^*(i)\}_{i \in I_1}$ is selected.
6. A random sample of size $m \times f_1(0)$ with replacement from $\{TFPG_i^*(i)\}_{i \in I_1}$ is generated.

A recent study by Firpo et al. (2009) argues that some of the results in Machado and Mata (2005) may be biased since this technique can also change the distribution of other covariates which are correlated with the variables studied. This problem is addressed by modifying Point 3 of the technique. Instead of considering the rows z^*, the average of the unconditional quantile regression $\bar{z}^*$ is used, since $E(Y|X) = X\beta$ leads to $E(Y) = E(X|\beta)$.

If (4.4) is specified in the correct way, the parameters of the estimation can be used to simulate the conditional TFP growth changes from $TFPG(1, \beta_1 TFPG^*(1))$ to $TFPG(1, \beta_0 TFPG^*(1))$ by computing

- *Total Growth:* $y_1^1 - y_0^0 = \overline{Cict_1} - \overline{Eict_1} =$
$$TFPG\left(1, \beta_1 \overline{TFPG}^*(1)\right) - TFPG\left(0, \beta_0 \overline{TFPG}^*(0)\right) =$$
- *Capital Accumulation:* $\overline{Eict_1} - \overline{A_1 ict_1}$
$$TFPG\left(1, \hat{\beta}_1^{VRS} \overline{TFPG}^*(1)\right) - TFPG\left(1, \hat{\beta}_0^{CRS} \overline{TFPG}^*(1)\right)$$

- *Spillover Effects:* $\overline{Cict_1} - \left\{\lambda\overline{D_2ict_1} + (1-\lambda)\,\overline{D_1ict_1}\right\}$

$$+TFPG\left(1, \hat{\beta}_0^{CRS}\overline{TFPG}^*(1)\right) - \\ \left\{\lambda TFPG\left(1, \hat{\beta}_1^{CRS}\overline{TFPG}^*(0)\right) + (1-\lambda)\,TFPG\left(1, \hat{\beta}_1^{VRS}\overline{TFPG}^*(0)\right)\right\}$$

- *Technological Change:* $\left\{\overline{\lambda D_2ict_1} + (1-\lambda)\,\overline{D_1ict_1}\right\} - \overline{Eict_1}$

$$+\left\{\lambda TFPG\left(1, \hat{\beta}_1^{CRS}\overline{TFPG}^*(0)\right) + (1-\lambda)\,TFPG\left(1, \hat{\beta}_1^{VRS}\overline{TFPG}^*(0)\right)\right\} - TFPG\left(0, \hat{\beta}_0\overline{TFPG}^*(0)\right)$$

- *Residual:*

$$+\epsilon \tag{4.6}$$

Following (4.6), the difference in $\Delta TFPG$ can be decomposed into three parts. The first part is represented by the capital accumulation effects. The other two parts are based on the production function under CRS and VRS

$$\left\{\lambda TFPG\left(1, \hat{\beta}_1^{CRS}\overline{TFPG}^*(0)\right) + (1-\lambda)\,TFPG\left(1, \hat{\beta}_1^{VRS}\overline{TFPG}^*(0)\right)\right\},$$

i.e., an average, weighted by $\lambda \in [0, 1]$, of the densities that would result in $t = 0$, if the covariates of the productivity given by the technological change $\overline{TFPG}^*$ were distributed as in $t = 1$. Similar to the representation in the lower part of Figure 1, the technological representation of T^2 could be thought as a production function with several kinks, while technology T_1^* could be associated with an average of these kinks. For these reasons, I assume that the coefficients for CRS and VRS can be estimated using the estimations given by the OLS and QR regressions, respectively: $\beta^{CRS} = \beta^{OLS}$ and $\beta^{VRS} = \beta^{QR}$.

4.6. The Italian Case

4.6.1. The *Uni Credit Group* Dataset

The empirical analysis is based on two datasets (the 8^{th} and the 9^{th} waves) obtained by a survey (*Indagine sulle Imprese Manifatturiere*), organized by the Italian bank *Uni Credit Group*. The data has been collected to obtain a representation of industries, employees and geographical location for two 3-year periods (1998-2000 and 2001-2003) for a stratified sample of Italian manufacturing firms with more than 10 employees. The period considered corresponds to the period of initial adoption of new technologies in the Italian economy (Fabiani et al. (2005)). Moreover, all the Italian manufacturing firms with more than 500 employees are contained in the dataset. The survey has been integrated with the entire information from balance sheet data for each firm.

In addition to the disaggregation into 8,100 very small municipalities (*Comuni*) and 103 provinces (which are roughly the size of an American county), a new unit of observations for geographical space contained in the dataset is considered, namely the local labor system (*Sistemi Locali del Lavoro*, LLS). The LLS is defined by the Italian Statistical Office (ISTAT), and Sforzi (2000) and has the following characteristics: 1) it is spatially interconnected *Comuni* and reachable on the degree of working-day commuting day by the resident population, 2) more than 75% of inhabitants in the LLS work within the LLS itself, and 3) local labor markets are considered such that local units of production primarily employ local workforces. In this Chapter, I use LLS as a measure of geographical space. Figures 4.2 and 4.3 compare the differences between the Italian administrative division (left hand side) and the LLS (right hand side), where the last one provides a more detailed division of the country. The black areas display how the district areas overlap. Most located in the northern area of the country, were free cities during the Middle ages (Guiso et al. (2008)) and are located on the main physical infrastructural networks.[12] Sections 6 and 7 compare the spillover emanated in an LLS with the new definition of network space.

Tables 4.1 and 4.2 provide some descriptive statistics for the two periods analyzed, which are divided into categories of general information, employment, investment, internationalization and network. The upper part of the tables show that the average age of the firms is about 23 years. This result indicates that most of them started their own activity during the 1980s period of the Italian economic boom. Most firms are controlled by another company and about 3% operate in a district area. Regarding geographical location, about 70% of the firms are located in the northern area. Other pieces of information are related to the employment structure; firms have an average of 370 employees and a very low share of white-collar and skilled workers with respect to the total workers. About 20% of the firms are engaged in exporting activity while 5% delocalize or outsource. The statistics are also divided into traditional and innovative firms, following the Pavitt classification,[13] contained in the dataset. Since this study focuses on innovative firms, the regression analysis is performed excluding the traditional firms.[14]

[12] The red line represents the railway lines, and green line represents highways.

[13] Pavitt (1984) distinguishes among traditional, scale, specialized, and high technological sectors.

[14] Descriptive statistics suggests that there is no relevant difference between traditional and innovative firms when considering the two dataset samples. The QR analysis has also been performed for the entire datasets with similar results.

4.6.2. Quantile Regression Analysis

For estimating the basic specification with the QR regressions, it can be useful to consider the panel structure of the data. First, because the dataset contains at least three years of observations for each firm, the unobserved characteristics can be ruled out to estimate the first year difference. This can be rewritten as (4.1):

$$\Delta TFPG_i\,(t) = \beta_0 + \beta_0 \Delta\epsilon_i\,(t) + \beta_1 \Delta\epsilon\,(t) + \beta_2 \Delta\overline{TFPG}_{S\ TECH}\,(t) + \upsilon_i\,(t) \tag{4.7}$$

Moreover, I add the constant β_0 to take a long-run effects into account. Some problem can arise in the estimation of the spillover coefficient β_2. First, there may be a self-selection problem. Firms can have an incentive to locate each other because of lower adoption costs in a particular location. Even if Guiso and Schivardi (2007) (referring to a survey run by the Bank of Italy in which firm location is mostly dictated by a founder's birthplace than by other economic reasons and the presence of pecuniary costs in adjusting and financial constraints can mitigate a self-selection) support the hypothesis that this does not apply to Italian units of production, this problem can solved by exploring the panel characteristics of the data. This will control for any fixed-level characteristics.

In addition, the so called "reflection problem," introduced by Manski (1993), can arise. Individual agents in a group are likely to be related to the average actions of members of the same group, such that identification problems may arise when disentangling the effects of individual choices with respect to the characteristics of the others. This problem is avoided by considering $\overline{TFPG}$ as the maximum of TFP in a specific set of industries and not an average of TFP growth. However, this problem should not be significant. From a theoretical point of view, the introduction of specific shocks can solve this type of problem. Brock and Durlauf (2001) stressed that this econometric problem appears only when all regressors affect the mean of both group and individual decision to enter.

Finally, another important problem is related to unobserved common shocks, which can affect the productivity of a firm: for example, ICT producers could be affected by innovations or by the introduction of a new product. For example, a new type of mobile phone can increase productivity but can also be confused with pure technological spillovers. I can rule out this possibility after considering in (4.7) the maximum productivity growth originating from the same sector but that is outside the technological space (for example, considering the LLS on the border) or in different sectors to find that those variables are not significant or equal to zero.[15]

Figure 4.4 suggests that a QR regression analysis is better than an OLS technique: the upper part depicts the kernel estimates for dependent and explanatory variables for the averages of the periods 1998-2000 and 2001-2003. For both periods, the multimodal distributions for productivity and frontier productivity confirm the predictions described in Section 4. Moreover, while the first peak is not affected by change, the second peak

[15] When I consider the LLS on the border the coefficients estimated are almost significant with an average equal to 0.0001, while the coefficients obtained exploiting the information from different sector are not significant. Guiso and Schivardi (2007) also exclude unobserved commons shocks for adjustment in employment.

shifts on the right. On the other side, the common and specific shocks maintain a unimodal distribution, suggesting a Schumpeterian reallocation in productivity from the least to the most productive unit of productions. Finally, the need for QR regression is also confirmed by the lower part of Figure 4.4, where the cumulative density function with respect to the fraction of the data for the quantiles $0.05 \leq q \leq 0.95$ is shown, which is the subsample of the dataset.

Before analyzing the QR results, I run the separated probit for IT, C and ICT, and the bivariate probit regression introduced in Section 4.4 for the two periods 1998-2000 and 2001-2003, considering some variables already used in the literature (Matteucci et al. (2005)). The average share of investment in new technologies out of total investment for each LLS is displayed in Figure 4.5 for ICT, C, and IT, respectively, in the two different periods. The figure shows that there is heterogeneity in the deepening of new technology investment. Even if the highest percentages are mostly concentrated in the northern part of the country, there are areas, most of the time districts, in which investment in new technologies is higher than 70%.[16] The results are reported in Tables 4.3 and 4.4. All specifications also consider LLS and industries dummies, which are not displayed. The ρ are statistically different from zero, suggesting the use of the bivariate probit. Even if the results from the probit regressions do not provide significant results, especially for the period 1998-2000, as most of the effects are captured by the geographical and industry dummies, the results from the bivariate probit regression suggests that bigger firms in term of value added, older, located in the northwest regions and participating in international activities are more likely to invest in IT and C. Finally, results derived from the predicted probabilities are compared with the TFPG in Figure 4.6, where it is possible to observe the positive correspondence between the average predicted propensity in ICT investment, estimated using the bivariate probit, and the TFP growth in each LLS.[17] In this case, firms with a propensity higher than the median both in IT and C are assumed to derive positive externalities from LLS and other technological firms.

[16] Other statistics concerning ICT investment are reported in Table 5 of Appendix J.

[17] The same results that ICT increases productivity are observed exploiting the DiNardo et al. (1996) approach. Output available upon request.

Figure 4.1.: The effect of ICT spillovers in the New Economy (upper part) and the Malmquist index (lower part)

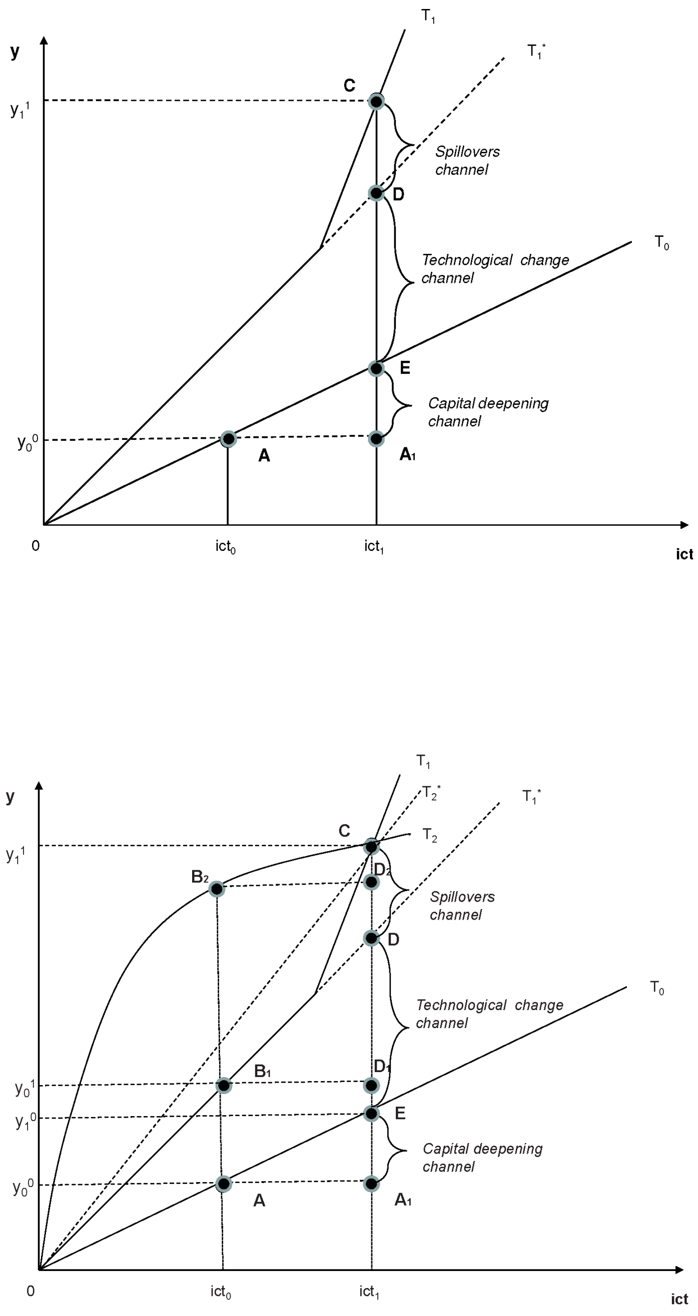


Figure 4.2.: Italian provinces

Figure 4.3.: Districts and public infrastructures

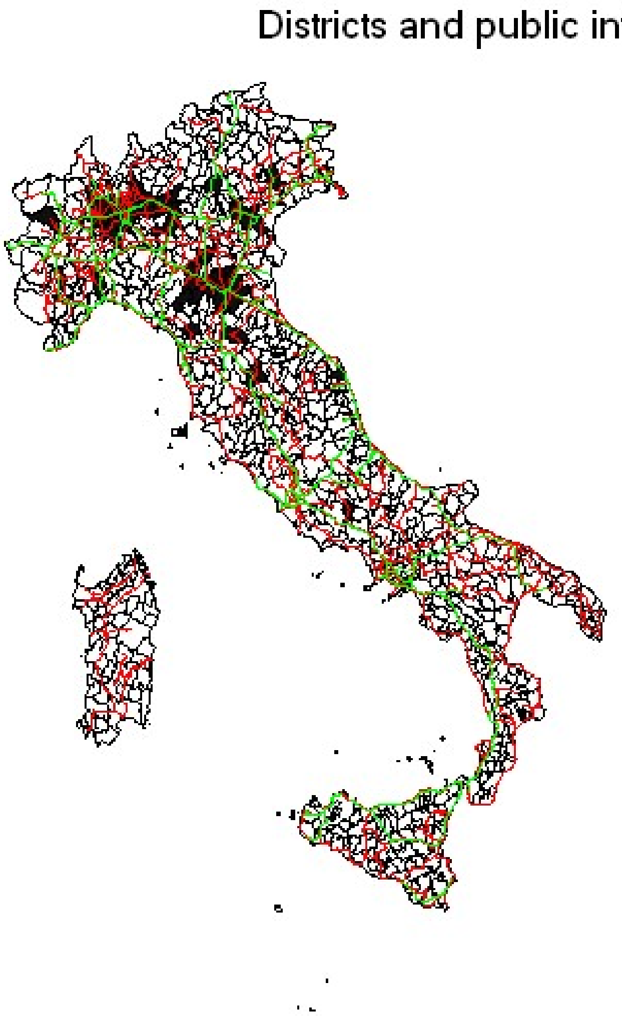


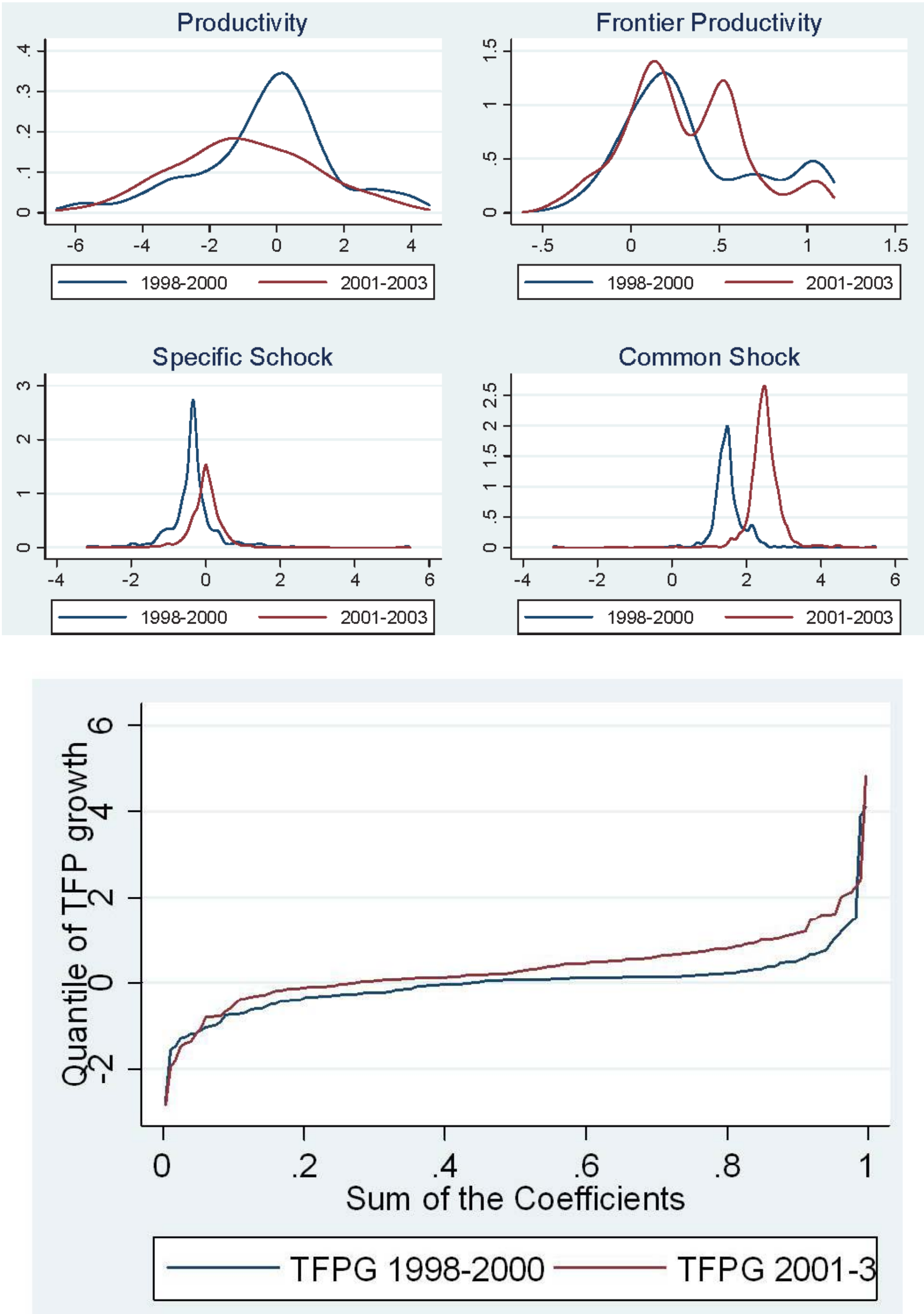
Table 4.1.: Descriptive statistics: 2000

2000										
	Entire Sample					Non Traditional				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**
A. General Information										
Age	23.70	17.83	0	182	4,315	23.65	17.21	1	182	2,057
Controlled	0.95	0.21	0	1	4,414	0.95	0.21	0	1	2,111
District	0.03	0.18	0	1	4,414	0.03	0.17	0	1	2,111
North East	0.13	0.34	0	1	4,414	0.16	0.37	0	1	2,111
North West	0.11	0.32	0	1	4,414	0.12	0.32	0	1	2,111
Centre	0.07	0.25	0	1	4,414	0.05	0.22	0	1	2,111
South	0.04	0.20	0	1	4,414	0.03	0.16	0	1	2,111
B. Employment										
Employees	148.58	371.91	4	5768	854	175.16	390.88	7	3791	400
$WhiteColl./TOT$	0.38	0.19	0.04	1	985	0.41	0.19	0.04	1	565
$Skill/TOT$	0.06	0.07	0	0.625	2,510	0.07	0.08	0	0.63	1,280
Hired	0.88	0.33	0	1	4,184	0.89	0.31	0	1	2,014
Fired	35.09	217.00	0	6972	2,561	42.68	266.92	0	6972	1,282
Wage Flex	0.16	0.37	0	1	4,414	0.19	0.39	0	1	2,111
C. Investment										
$Inv./Y$	0.24	3.04	0.00	79.59	790	0.17	1.62	0	31.44	376
Innovation	0.56	0.50	0	1	4,414	0.62	0.49	0	1	2,111
R&D	0.38	0.49	0	1	4,414	0.47	0.50	0	1	2,111
ict	0.81	0.40	0	1	4,414	0.84	0.37	0	1	2,111
it	0.78	0.41	0	1	4,414	0.81	0.39	0	1	2,111
c	0.77	0.42	0	1	4,414	0.80	0.40	0	1	2,111
$DEBT/Y$	0.22	0.17	0	0.67	854	0.20	0.16	0	0.66	400
D. Internationalization										
Export	0.23	0.42	0	1	4,414	0.26	0.44	0	1	2,111
Delocalization	0.02	0.14	0	1	4,414	0.01	0.12	0	1	2,111
Outsourcing	0.07	0.25	0	1	4,414	0.08	0.27	0	1	2,111
Foreign Service	0.05	0.21	0	1	4,414	0.05	0.22	0	1	2,111
E. Network										
Consortium	0.10	0.30	0	1	4,396	0.09	0.28	0	1	2,103
R&D with firms	0.99	0.11	0	1	4,414	0.98	0.12	0	1	2,111
Deloc. Aquisition	0.02	0.13	0	1	4,342	0.03	0.17	0	1	2,082
Deloc. Cession	0.01	0.09	0	1	4,354	0.01	0.11	0	1	2,085
Deloc. Technology	0.04	0.20	0	1	4,346	0.05	0.22	0	1	2,079
Deloc. Investment	0.02	0.15	0	1	4,335	0.02	0.15	0	1	2,072

Table 4.2.: Descriptive statistics: 2003

2003										
	Entire Sample					Non Traditional				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**
A. General Information										
Age	28.31	18.94	1	174	1,390	28.09	18.68	1	174	1,330
Controlled	0.90	0.30	0	1	1,498	0.90	0.30	0	1	1,435
District	0.07	0.27	0	1	1,498	0.08	0.27	0	1	1,435
North East	0.43	0.49	0	1	1,498	0.43	0.50	0	1	1,435
North West	0.32	0.47	0	1	1,498	0.32	0.47	0	1	1,435
Centre	0.15	0.36	0	1	1,498	0.15	0.36	0	1	1,435
South	0.10	0.30	0	1	1,498	0.10	0.30	0	1	1,435
B. Employment										
Employees	211.92	569.47	1	11,437	1,475	214.64	580.01	1	11,437	1,415
$WhiteColl./TOT$	0.08	0.08	0	1	1,493	0.08	0.08	0	1	1,430
$Skill/TOT$	0.07	0.09	0	0.85	1,230	0.07	0.09	0	0.85	1,175
Hired	0.88	0.32	0	1	1,481	0.88	0.33	0	1	1,420
Fired	27.47	112.93	0	2,876	1,490	27.45	114.64	0	2,876	1,428
Wage Flex	0.55	0.50	0	1	1,498	0.55	0.50	0	1	1,435
C. Investment										
$Inv./Y$	38.12	50.28	0	533.80	1,366	38.32	50.87	0	533.80	1,311
Innovation	0.76	0.43	0	1	1,498	0.76	0.43	0	1	1,435
R&D	0.56	0.50	0	1	1,498	0.56	0.50	0	1	1,435
ict	0.82	0.39	0	1	1,498	0.82	0.38	0	1	1,435
it	0.73	0.45	0	1	1,498	0.73	0.45	0	1	1,435
c	0.36	0.48	0	1	1,498	0.36	0.48	0	1	1,435
$DEBT/Y$	0.16	0.16	0	0.70	1,410	0.16	0.16	0	0.70	1,354
D. Internationalization										
Export	0.79	0.41	0	1	1,486	0.79	0.41	0	1	1,423
Delocalization	0.06	0.24	0	1	1,498	0.06	0.25	0	1	1,435
Outsourcing	0.19	0.40	0	1	1,498	0.19	0.40	0	1	1,435
Foreign Service	0.19	0.39	0	1	1,498	0.19	0.39	0	1	1,435
E. Network										
Consortium	0.12	0.32	0	1	1,446	0.11	0.32	0	1	1,386
R&D with firms	0.88	0.33	0	1	1,498	0.87	0.33	0	1	1,435
Deloc. Aquisition	0.21	0.40	0	1	1,420	0.21	0.40	0	1	1,361
Deloc. Cession	0.01	0.11	0	1	1,420	0.01	0.12	0	1	1,362
Deloc. Technology	0.07	0.26	0	1	1,419	0.07	0.26	0	1	1,360
Deloc. Investment	0.04	0.20	0	1	1,420	0.04	0.20	0	1	1,361

Figure 4.4.: Kernel distribution of the dependent variable and the regressors (upper part) and TFP growth cumulative density function



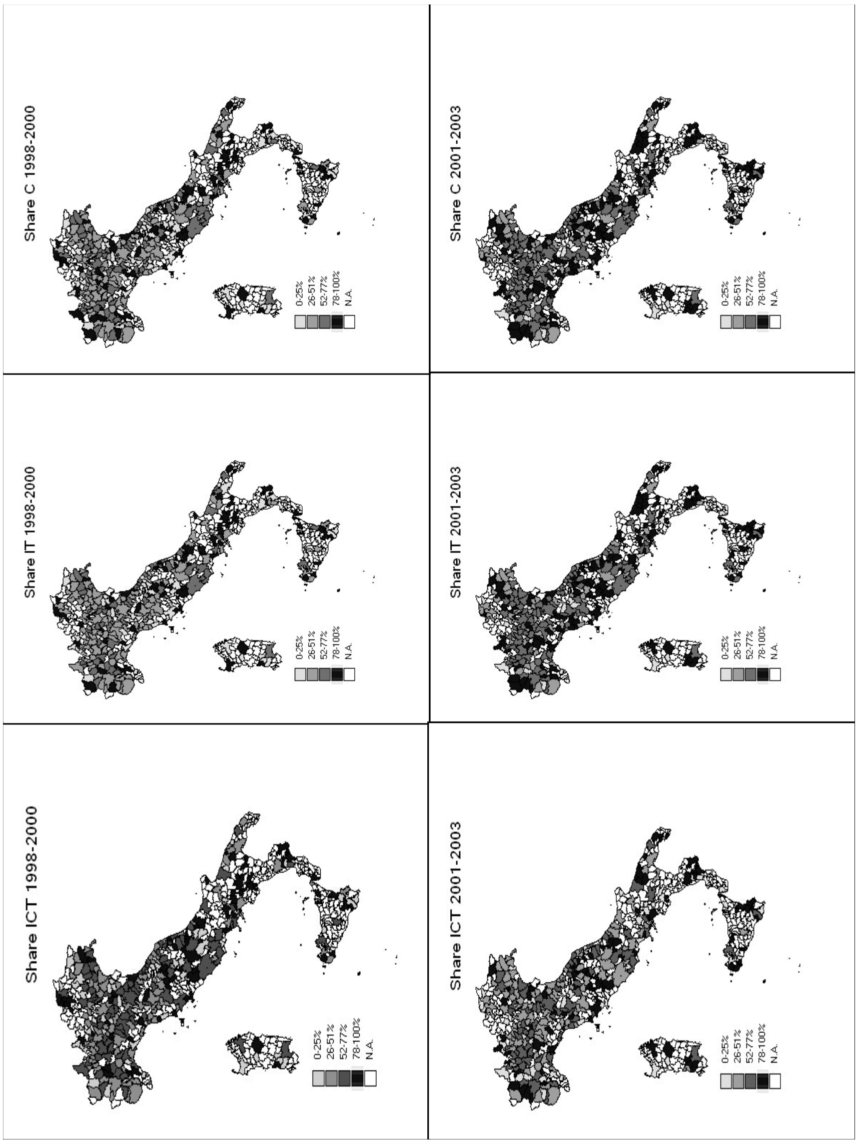


Figure 4.5.: Ratios of new technology investment out total investments (in %)

Table 4.3.: Bivariate probit: First Part

	1998-2000				2001-2003			
	Probit			Biv. Probit	Probit			Biv. Probit
Dependent Variable	*ICT*	*IT*	*C*	*IT&C*	*ICT*	*IT*	*C*	*IT&C*
				(*IT*)				(*IT*)
Export	0.449	0.657	0.239	0.502	0.090	0.179	-0.006	0.200
	(0.366)	(0.387)	(0.260)	(0.329)	(0.112)	(0.102)	(0.106)	(0.103)
ln(VA)	0.115	-0.003	0.146*	0.023	0.047	0.093*	0.088*	0.099*
	(0.092)	(0.086)	(0.061)	(0.086)	(0.044)	(0.039)	(0.035)	(0.041)
Age	0.006	0.008		0.008	0.006*	0.007**		0.006**
	(0.006)	(0.006)		(0.007)	(0.003)	(0.002)		(0.002)
Controlled	-0.094	-0.067		-0.119	-0.451*	-0.255		-0.308
	(0.363)	(0.310)		(0.331)	(0.207)	(0.171)		(0.166)
District	0.081	0.119	0.452	0.165	0.427*	0.274	0.139	0.296
	(0.522)	(0.523)	(0.429)	(0.478)	(0.202)	(0.164)	(0.133)	(0.162)
Innovation	0.136	0.218	0.003	0.186	0.021	0.347	0.291	0.343
	(0.208)	(0.195)	(0.163)	(0.200)	(0.301)	(0.265)	(0.205)	(0.264)
Foreign Service	-0.372	-0.405	-0.053	-0.366	0.070	0.011	-0.207	-0.032
	(0.442)	(0.400)	(0.253)	(0.461)	(0.260)	(0.217)	(0.186)	(0.216)
R&D	0.419*	0.369	0.046	0.346	0.087	0.154	-0.072	0.184
	(0.213)	(0.204)	(0.163)	(0.213)	(0.118)	(0.107)	(0.095)	(0.106)
North West	0.236	0.165	0.078	0.264	0.065	0.238*	0.252**	0.235*
	(0.495)	(0.480)	(0.284)	(0.492)	(0.105)	(0.096)	(0.097)	(0.095)
North East	-0.339	-0.509	0.018	-0.291	-0.000	-0.005	0.127	-0.013
	(0.408)	(0.415)	(0.315)	(0.364)	(0.124)	(0.110)	(0.099)	(0.111)
South	-0.263	-0.330	0.063	-0.157	0.218	0.039	0.124	0.016
	(0.437)	(0.442)	(0.397)	(0.415)	(0.125)	(0.117)	(0.115)	(0.117)
LLS	0.000	0.001	-0.001*	0.001	0.296*	0.188	0.069	0.184
	(0.001)	(0.001)	(0.001)	(0.001)	(0.134)	(0.123)	(0.119)	(0.123)
Industry	0.006	0.030	0.186	0.106	-0.165	-0.183	-0.186	-0.197
	(0.147)	(0.142)	(0.109)	(0.136)	(0.162)	(0.153)	(0.161)	(0.153)
Debt/Y	-0.772	-0.480	0.011	-0.072	-0.000	-0.000	-0.000	-0.000
	(0.548)	(0.521)	(0.435)	(0.548)	(0.000)	(0.000)	(0.000)	(0.000)
Outsourcing	-0.062	-0.280	-0.051	-0.095	0.057	0.095	0.162*	0.073
	(0.431)	(0.364)	(0.294)	(0.399)	(0.074)	(0.068)	(0.065)	(0.069)
Deloc. Aquis.	0.315		0.110		0.226	0.356	0.391	0.374
	(0.356)		(0.357)		(0.293)	(0.258)	(0.242)	(0.262)
Deloc. Cess.	-0.612		0.646		-0.278		0.042	
	(0.672)		(0.631)		(0.164)		(0.115)	
Deloc. Tech.	-0.227		0.080		0.052		0.203*	
	(0.458)		(0.304)					
Firm Inv.			-0.583	5.745***	(0.489)		(0.311)	
			(0.621)	(0.396)	0.383		0.127	
R&D firm			-0.270		(0.226)		(0.151)	
			(0.531)		0.444***	0.413***	0.044	0.398***
Constant	-0.122	0.516	-1.285	0.102	(0.519)	(0.425)	(0.362)	(0.411)
	(1.019)	(0.955)	(0.853)	(0.920)				

Table 4.4.: Bivariate probit: Second Part

	1998-2000				2001-2003			
	Probit			Biv. Probit	Probit			Biv. Probit
Dependent Variable				(C)				(C)
Export				0.257				0.012
				(0.265)				(0.107)
ln(VA)				0.143*				0.097**
				(0.061)				(0.036)
$Debt/Y$				0.075				0.325
				(0.439)				(0.247)
District				0.467				0.129
				(0.436)				(0.136)
Firm Inv.				-0.571				0.342
				(0.626)				(0.209)
Outsourcing				-0.061				-0.064
				(0.302)				(0.095)
Innovation				-0.002				0.251*
				(0.164)				(0.101)
Foreign Service				-0.077				0.133
				(0.260)				(0.100)
R&D firm				-0.132				0.054
				(0.486)				(0.111)
Deloc. Aquisition				0.065				0.196*
				(0.327)				(0.090)
Deloc. Cess.				0.867				0.003
				(0.467)				(0.274)
Deloc. Tech.				0.101				0.041
				(0.283)				(0.142)
Deloc. Inv.				0.543				0.094
				(0.337)				(0.095)
R&D				0.089				0.093
				(0.164)				(0.116)
North West				0.045				0.059
				(0.297)				(0.121)
North East				-0.042				-0.229
				(0.314)				(0.164)
South				0.046				-0.000
				(0.403)				(0.000)
Constant				-1.385				
				(0.828)				
ρ				0.9233***				0.899***
				(0.076)				(0.1666)
N	332	372	370	364	1,224	1,250	1,263	1,224

4.7. Empirical Analysis

An easy way to display the result from the QR analysis is a graphic representation of the coefficient of the analysis of (4.1) $\hat{\beta}_i(\theta)$, $i = 1, \ldots, 4$ for $\theta \in (0, 1)$ (represented by the dotted lines), the correspondent 95% heterogeneity consistent confidence interval bands obtained after a bootstrap procedure with 400 iterations, following the procedure as Hendricks and Koenker (1982) and Cameron and Trivedi (2008) (depicted by the smaller lines), and the β obtained by the OLS mean regression (solid horizontal line).

Figures 4.7 and 4.8 show the results for the QR regressions for the models in which the technological space is assumed to be a LLS or the new network space. The first two columns display the results for 1998-2000 and 2001-2003, while the third column displays the differences along time. Concerning both periods, it seems that spillover effects and long-run efficiency decrease and increase, respectively, as the quantile regression moves up through the TFPG distribution. Conversely, the shocks seem to have a more stable impact for each quantile. The results suggest that the benefits of spillover effects should be more important at the lowest than at the highest part of the distribution, as shocks seem to have a more pronounced impact in the middle of the distribution. Finally, when the new definition of technological space is considered, the value of the coefficients is generally smaller than in the first case.

4.7.1. Counterfactual Analysis

Following the procedures described in Sections 4 and 5, a number of replication m equal to 1,000 are considered to decompose the changes in TFP growth into changes attributable to the variations in the covariates (i.e., the capital accumulation effect), the coefficient divided into a spillover effect and a technological change effect. Figures 4.10 and 4.11 plot the various differences between pairs of distribution. The first graph displays differences of the densities of the TFP growths $TFPG\left(1, \beta_1 \overline{TFPG}^*(1)\right) - TFPG\left(0, \beta_0 \overline{TFPG}^*(0)\right)$ and the one of the coefficients as in (4.6). This shows that both the covariates and coefficients contributed to a shift of the productivity distribution to the right. On the other hand, while the impact of the capital accumulation channel is quite insignificant (second graph), the total factor productivity growth channel seems to be the most important contributor in the shift of the production function. While the OLS estimation does not give strong estimates, a higher influence is displayed when the spillover effects are estimated considering the QR analysis. These effects are more pronounced providing the two different distributions.

4.8. Conclusion

In this Chapter, I suggest that the econometric models for studying R&D spillovers are inappropriate for detecting the externalities created by ICT. I therefore propose a new method based on the counterfactual properties of the Malmquist index and the Machado and Mata (2005) procedure to decompose in the TFP growth distribution into a capital accumulation, a pure technological change and a spillover effect channel over two time periods. The main assumption is that the introduction of new technological investment changes the structure in the production function by introducing kinks in the technological frontier. In addition, investment in communication allows firms to be part of a network different from the one constituted by neighborhood.

This methodology is applied to an Italian manufacturing dataset for the period 1998-2003, a period in which firms began investing in ICT. Given the particular structure of the Italian economy, this controls for econometric issues like the reflection problem. My estimation suggested that if the technological space is constructed following the classic definition of geographical space, TFP is completely driven by pure technological change. On the other hand, once the space is defined considering a new type of networking, spillover effects can play an important role. The most productive firms are also the foremost recipients of ICT spillovers. This should suggest that both ICT producers and users of new technologies can benefit from ICT. Furthermore, a policy implication is that IT goes hand in hand with C in augmenting TFP.

Figure 4.6.: Propensity LLS

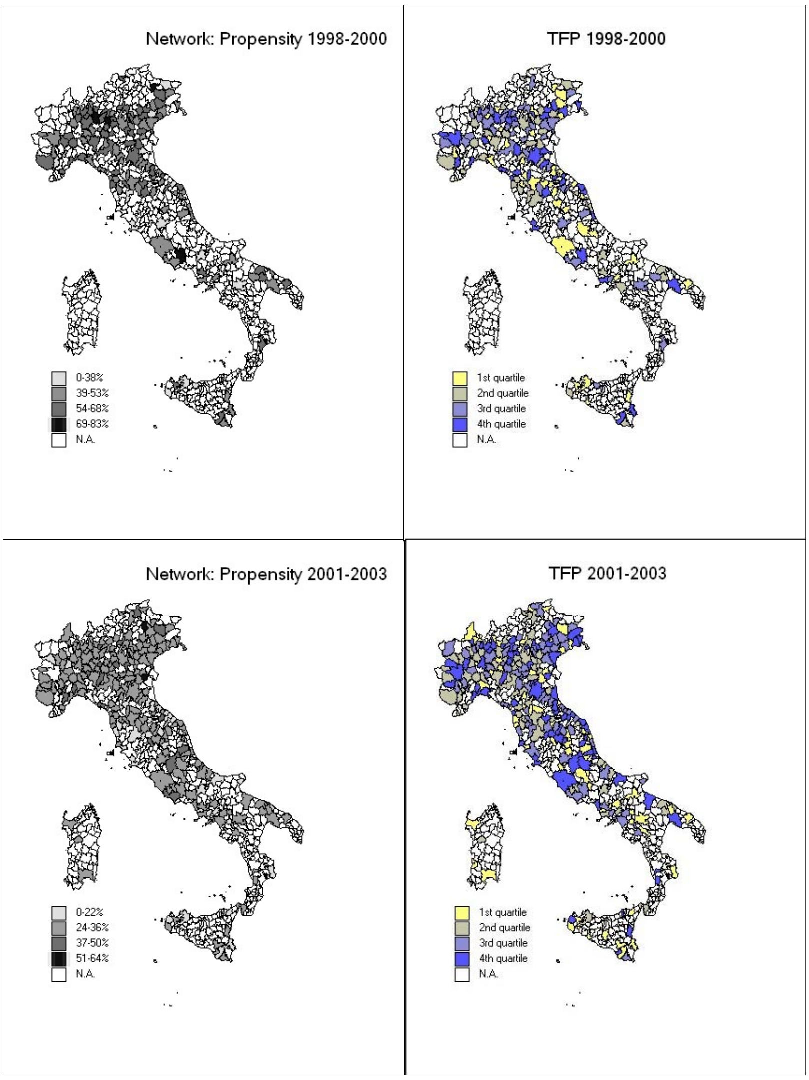


Figure 4.7.: LLS as technological space. Quantile regressions with 95% confidence intervals for the deciles; OLS (conditional mean) is represented by solid horizontal line.

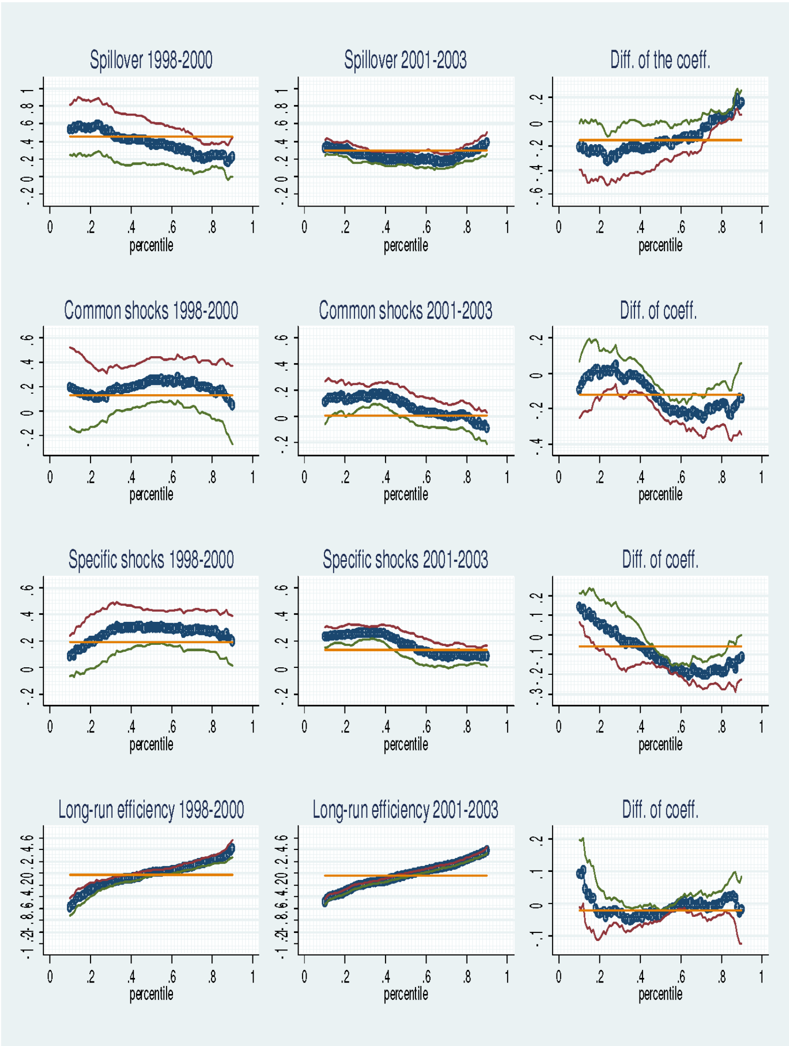


Figure 4.8.: ICT network as technological space. Quantile regressions with 95% confidence intervals for the deciles; OLS (conditional mean) is represented by solid horizontal line.

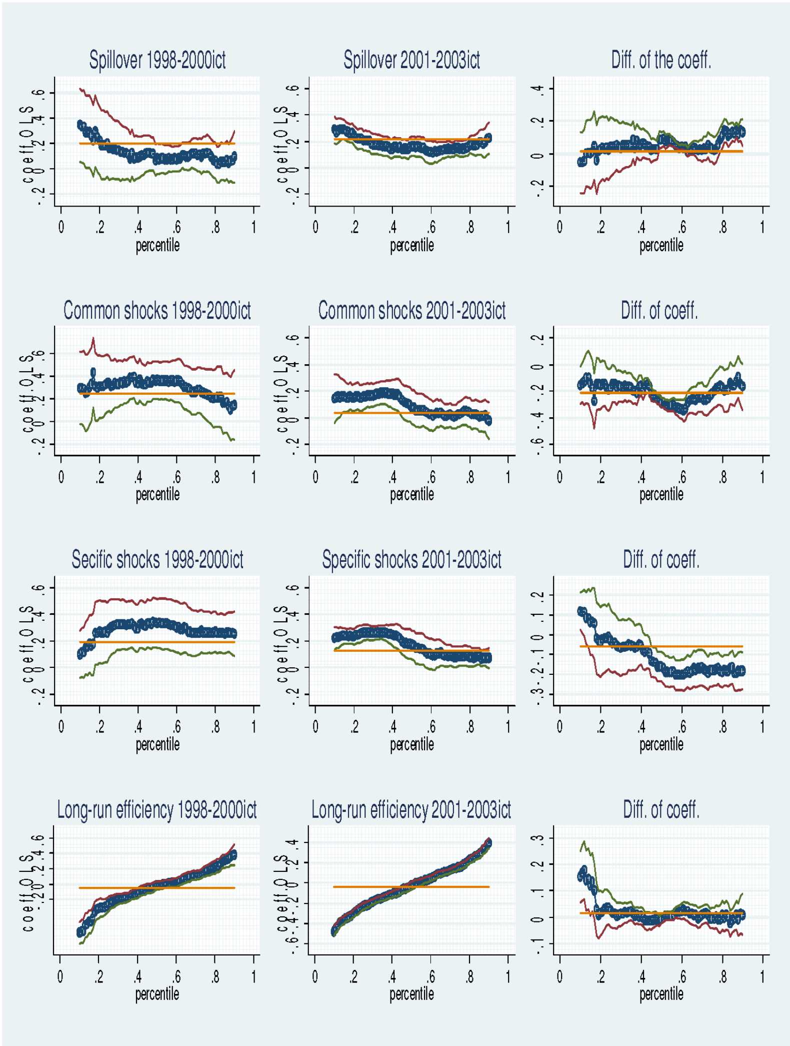


Figure 4.9.: Difference in technological space. Quantile regressions with 95% confidence intervals for the deciles; OLS (conditional mean) is represented by solid horizontal line.

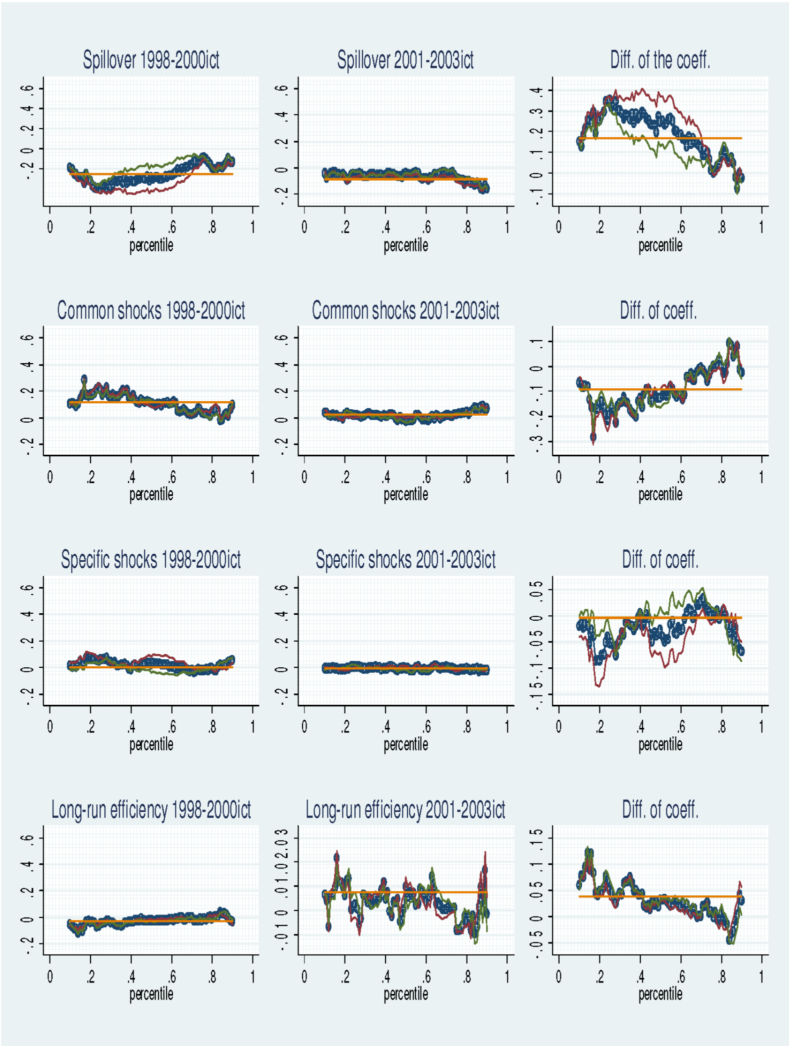
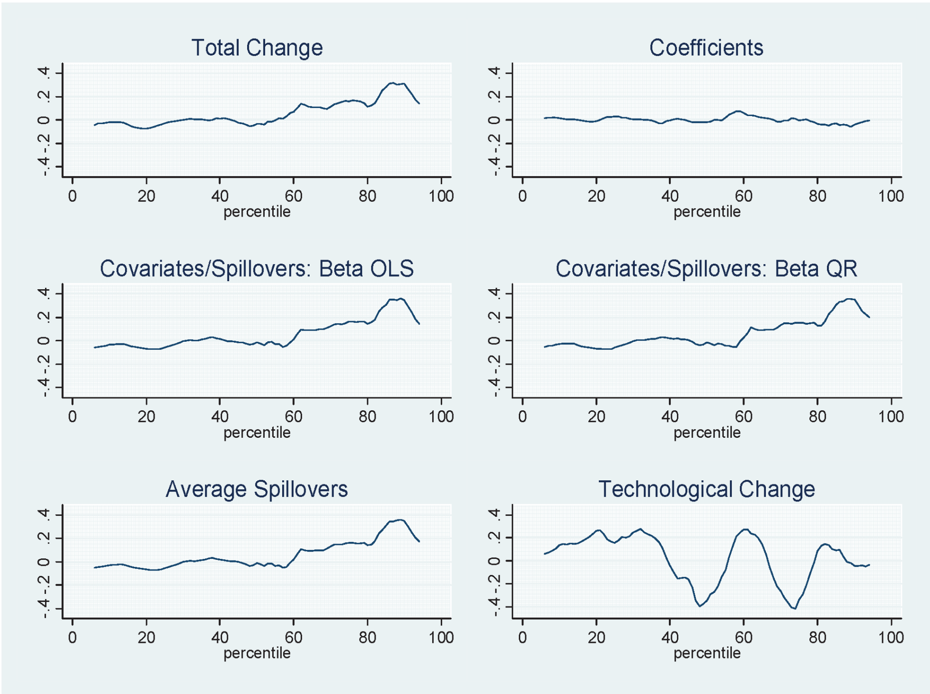


Figure 4.10.: Counterfactual decomposition

Figure 4.11.: The role played by the technological space



A. Appendix to Chapter 2

Appendix A: The Stochastic Growth Model

A1. First Order Conditions and Decentralized Market Equilibrium

Let λ_t denote the Lagrange multiplier corresponding to the periodic resource constraint (2.6). The first-order conditions for the household are, for $t \geq 0$:

$$C_t: \ \lambda_t = \frac{1}{C_t} \tag{A.1}$$

$$K_{t+1}: \ \lambda_t = \beta E_t \left[\lambda_{t+1} \left((1-\delta_{t+1}) + \kappa_{t+1} U_{t+1}\right)\right] \tag{A.2}$$

$$N_t: \ \theta(1-N_t)^{-\eta} = \lambda_t \omega_t \tag{A.3}$$

$$U_t: \ BU_t^{\chi-1} = \kappa_{t+1} \tag{A.4}$$

First-order conditions for the firms

$$N_t: \ (1-\alpha) A_t (U_t K_t)^{\alpha} N_t^{-\alpha} = \omega_t \tag{A.5}$$

$$K_t: \ \alpha A_t U_t^{\alpha} K_t^{\alpha-1} N_t^{1-\alpha} = \kappa_t U_t \tag{A.6}$$

the production function

$$Y_t = A_t U_t^{\alpha} K_t^{\alpha} N_t^{1-\alpha} \tag{A.7}$$

and the aggregate resource constraint (since $\omega_t N_t + \kappa_t U_t K_t = Y_t$).

$$K_{t+1} = (1-\delta_t) K_t + Y_t - C_t \tag{A.8}$$

The equilibrium of this decentralized economy is defined as the sequences of wages $\{\omega_t\}$, rental prices for capital $\{\kappa_t\}$, output $\{Y_t\}$, consumption $\{C_t\}$, employment $\{N_t\}$, capital stocks $\{K_{t+1}\}$, and the capacity utilization rate $\{U_t\}$ such that equations (A.1)-(A.8) hold for $t \geq 0$ plus a suitable transversality condition to guarantee that the capital stock path is indeed consistent with utility maximization. The equilibrium of the problem will be, due to the first and second welfare theorems, unique and equivalent to the one chosen by a social planner with the objective of maximizing the utility of the representative household.

A2. Detrended version of Equilibrium

Steady state values of the model's variables are denoted by an upper bar. In the steady state $\bar{X}_{t+1} = (1+g)\,\bar{X}_t$ for $X \in \{C, I, Y, K\}$ and $\bar{A}_{t+1} = \psi \bar{A}_t$. We define detrended values of the variables of interest such that $\widetilde{X}_t \equiv X_t/\overline{X}_t$. The following equations characterize the equilibrium of this transformed economy:

$$\frac{\theta \tilde{C}_t}{(1-N_t)^\eta} = (1-\alpha)\,\gamma_t U_t^\alpha \tilde{K}_t^\alpha N_t^{-\alpha} \tag{A.9}$$

$$1 = E_t\left[\beta \frac{\tilde{C}_t}{\psi \tilde{C}_{t+1}} R_{t+1}\right] \tag{A.10}$$

$$\alpha\gamma_t \left(\frac{\tilde{K}_t}{N_t}\right)^{\alpha-1} = BU_t^{\chi-\alpha} \tag{A.11}$$

$$\psi \tilde{K}_{t+1} = (1-\delta_t)\,\tilde{K}_t + \tilde{Y}_t - \tilde{C}_t$$

The first equation characterizes intratemporal optimality of time across alternative uses in production and leisure; the second is the familiar Euler equation which arbitrages expected intertemporal rates of substitution and transformation in expectation, where the latter is defined by $R_{t+1} = \alpha\gamma_t \left(U_t\widetilde{K_t}\right)^{\alpha-1} N_t^{1-\alpha}$ and represents the gross rate of return on holding a unit of capital from period t to period $t+1$. The last equation is the periodic resource constraint of the economy, given the production function and competitive factor remuneration. Given that this economy fulfills the conditions of the first welfare theorem, it would also characterize the optimal choice of a central planner maximizing (2.5) subject to the resource constraints (2.6) and the initial condition K_0.

A3. The Steady State

To solve for the non-stochastic steady state, let $\gamma_t = 1$ and $\tilde{K}_{t+1} = \tilde{K}_t = \bar{K}$. We obtain the following equations:

$$\frac{\theta \bar{C}}{(1-\bar{N})^\eta} = (1-\alpha)\,\bar{U}^\alpha \bar{K}_t^\alpha \bar{N}^{-\alpha} \tag{A.12}$$

$$1 = \frac{\beta}{\psi}\bar{R} \tag{A.13}$$

$$\alpha \left(\frac{\bar{K}}{\bar{N}}\right)^{\alpha-1} = B\bar{U}^{\chi-\alpha} \tag{A.14}$$

A4. Log Linearization

Using the convention that $\widehat{x} = (x-\overline{x})/\overline{x}$ denote deviations from steady state values, the log-linearized first order condition for labor supply can be written as

$$\hat{c}_t - \left(\alpha + \frac{N}{1-N}\eta\right)\hat{n}_t = \gamma_t + \alpha\left(\hat{u}_t + \hat{k}_t\right) \tag{A.15}$$

The resource constraint is:

$$\frac{\bar{C}}{\bar{K}}\hat{c}_t + \psi\hat{k}_{t+1} = (1-\delta)\,\hat{k}_t - \chi\hat{u}_t + \alpha\frac{\bar{Y}}{\bar{K}}\hat{k}_t + (1-\alpha)\,\frac{\bar{Y}}{\bar{K}}\bar{N}\hat{n}_t + \frac{\bar{Y}}{\bar{K}}\hat{\gamma}_t \tag{A.16}$$

and the Euler equation becomes

$$0 = E_t\beta\left[\hat{c}_t + \hat{c}_{t+1} + \beta\bar{r}\left[\hat{\gamma}_{t+1} - (1-\alpha)\left(\hat{k}_{t+1} - \hat{n}_{t+1}\right) - \chi\hat{u}_t\right]\right] \tag{A.17}$$

A5. Model Calibration and Generation of the Synthetic Dataset

We calibrate the model to a quarterly setting using values typically used for simulating the US time series in the literature and discussed in Prescott (1986a) or Rebelo and King (1999). The values chosen for the parameters are presented in Table 4.

Appendix B: The Malmquist Index

B1. The Basics

The Malmquist index originates in measurement theory and is frequently applied to productivity estimation problems (see Malmquist (1953), Färe et al. (1989) and Färe et al. (1994)). Normalize observed output and capital by labour input $y_t = \frac{Y_t}{N_t}$ and $k_t = \frac{K_t}{N_t}$. If $f_t(k)$ defines the efficient level of production using k in time t, use the distance function $D_t\,(k_t, y_t) = y_t/f_t(k_t)$ to construct Malmquist index between periods 0 and 1 (Shepard (1970)):

$$M_0^1 = \underbrace{\sqrt{\frac{D_1\,(k_1, y_1)}{D_1\,(k_0, y_0)}}}_{\Delta\ efficiency}\underbrace{\sqrt{\frac{D_0\,(k_1, y_1)}{D_0\,(k_0, y_0)}}}_{\Delta\ technology} \tag{B.18}$$

B2. The Malmquist Index and the Solow Residual

Following Färe (1989), the Malmquist index can be decomposed as a product of change in efficiency at given technology, and technological change. Because the Solow decomposition assumes full efficiency, the Malmquist index is simply $\sqrt{\frac{D_0(k_1,y_1)}{D_0(k_0,y_0)}} = \sqrt{\frac{A_{t+1}}{A_t}}$. Figure B.1 depicts two data points $y_0^0 \equiv f_0(k_0)$ (point A) and $y_1^1 \equiv f_1(k_1)$ (point C), and two counterfactuals $y_0^1 \equiv f_1(k_0)$ (point B) and $y_1^0 \equiv f_0(k_1)$) (point D). Assuming constant returns and full efficiency, the log of the Malmquist index equals the log of the geometric mean of the average products in the two periods, or

$$\ln M_0^1 = \frac{1}{2}\ln\left(\frac{y_1^1}{y_0^0}\frac{y_1^0}{y_0^1}\right) = \underbrace{\frac{1}{2}\ln\left(\frac{y_1^1}{y_0^0}\right)}_{KNOWN} + \underbrace{\frac{1}{2}\ln\left(\frac{y_1^0}{y_0^1}\right)}_{UNKNOWN} \tag{B.19}$$

The Malmquist index puts a bound on possible evolution of TFP from period 0 to period 1, even when the capital stock is poorly measured or unobservable. Consider first the extreme case in which there is no capital accumulation in period 0, i.e. $k_0 = k_1$ and

$\ln M_0^1 = \frac{1}{2}\ln\left(\frac{y_1^1}{y_0^0}\right)$; in the other extreme, capital accumulation is identical to the growth of labor productivity, i.e. $\ln M_0^1 = \ln\left(\frac{y_1^1}{y_0^0}\right)$. We will employ the midpoint between these two values. We also consider the construction of the index when of negative technological progress: in this case, the lower bound is represented by the extreme case when capital accumulation is equal to the growth of labor productivity, i.e. $\ln M_0^1 = \ln\left(\frac{y_1^1}{y_0^0}\right)$, while the upper bound is represented by the case where there is no capital accumulation between the two periods.

B3. The Malmquist Index when Capacity Utilization is Observed

If data on capacity utilization are available, we can rewrite (B.19) in the case of full efficiency extending De Borger and Kerstens (2000):

$$M_0^1 = \frac{CU_0\left(k_0, U_0 k_0, y_0\right)}{CU_1\left(k_1, U_1 k_1, y_1\right)}\sqrt{\frac{D_0\left(k_1, y_1\right)}{D_0\left(k_0, y_0\right)}} \tag{B.20}$$

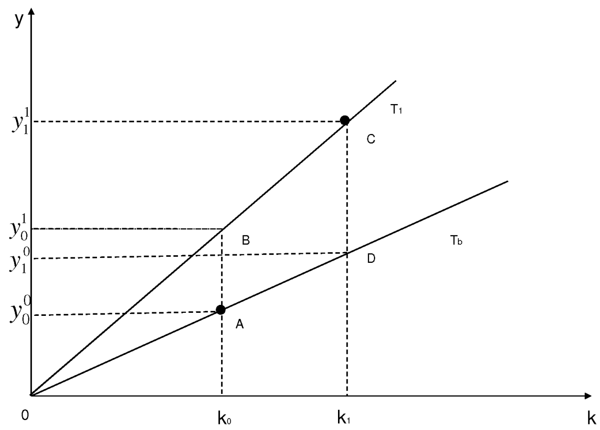
where $CU_t\left(k_t, U_t k_t, y_t\right) = \frac{D_t(U_t k_t, y_t)}{D_t(k_t, y_t)} \leq 1$ is the output efficiency measure removing any existing technical inefficiency. If production function is given by (2.3), we can rewrite $CU_t\left(k_t, U_t k_t, y_t\right) = \frac{A_t\left[(U_t K_t)^\alpha N_t^{1-\alpha}\right]/N_t}{A_t\left[K_t^\alpha N_t^{1-\alpha}\right]/N_t} = U_t^\alpha$ and recompute (B.19) as

$$\ln M_0^1 = \frac{1}{2}\ln\left(\frac{y_1^1}{y_0^0}\frac{y_1^0}{y_0^1}\right) + \alpha\ln\frac{U_0}{U_1} = \underbrace{\frac{1}{2}\ln\left(\frac{y_1^1}{y_0^0}\right) + \alpha\ln\frac{U_0}{U_1}}_{KNOWN} + \underbrace{\frac{1}{2}\ln\left(\frac{y_1^0}{y_0^1}\right)}_{UNKNOWN} \tag{B.21}$$

Table A.1.: Stochastic growth model: parameters and calibration values

Parameter	**Definition**	**Value**	**Source**
β	utility discount factor (quarterly)	0.985	Data
$\bar{R}$	average real interest factor (quarterly)	1.015	Data
$\bar{\gamma}$	technology	1	Theory
$\bar{\delta}$	depreciation rate of physical capital	0.015	Data
α	capital elasticity in production	0.36	Data
η	elasticity of periodic utility to leisure	0.85	Theory
θ	utility weight for leisure/consumption	2.1	Theory
$\psi = (1+g)^{1-\alpha}$	constant growth factor of technology	1.0075	Data
B	level parameter for capital depreciation rate	0.0255	Data
χ	elasticity of depreciation to capacity utilization	1.9	Data
ρ	autocorrelation of TFP term A_t	0.95	Theory

Figure B.1.: Construction of the Malmquist index in the full efficiency case



B. Appendix to Chapter 3

Appendix C: The Stochastic Growth Model

C1. First Order Conditions, Decentralized Equilibrium and Steady State

The following equations provide the first order conditions for optimal behavior of households and firms and characterize the decentralized market equilibrium, in which this regular economy is unique.

$$C_t : \lambda_t = \frac{1}{C_t} \tag{C.1}$$

$$K_{t+1} : \lambda_t = \beta E_t \left[\lambda_{t+1} \left((1-\delta) + \kappa_{t+1}\right)\right] \tag{C.2}$$

$$N_t : \frac{1}{(1-N_t)} = \lambda_t \omega_t \tag{C.3}$$

First-order conditions for the firms

$$N_t : (1-\alpha) A_t (K_t)^{\alpha} N_t^{-\alpha} = \omega_t \tag{C.4}$$

$$K_t : \alpha A_t K_t^{\alpha-1} N_t^{1-\alpha} = \kappa_t \tag{C.5}$$

the production function

$$Y_t = A_t K_t^{\alpha} N_t^{1-\alpha} \tag{C.6}$$

and the aggregate resource constraint (since $\omega_t N_t + \kappa_t K_t = Y_t$).

$$K_{t+1} = (1-\delta) K_t + Y_t - C_t \tag{C.7}$$

The equilibrium of this decentralized economy is defined as the sequences of wages $\{\omega_t\}$, rental prices for capital $\{\kappa_t\}$, output $\{Y_t\}$, consumption $\{C_t\}$, employment $\{N_t\}$, capital stocks $\{K_{t+1}\}$, such that equations (C1)-(C7) hold for $t \geq 0$ plus a suitable transversality condition to guarantee that the capital stock path is indeed consistent with utility maximization. The equilibrium of the problem will be, due to the first and second welfare theorems, unique and equivalent to the one chosen by a social planner with the objective of maximizing the utility of the representative household.

C2. The steady state

To solve for the non-stochastic steady state, let $\gamma_t = 1$ and $\tilde{K}_{t+1} = \tilde{K}_t = \bar{K}$. We obtain the following equations:

$$\frac{\theta \bar{C}}{(1-\bar{N})} = (1-\alpha)\,\bar{K}_t^{\alpha}\bar{N}^{-\alpha} \tag{C.8}$$

$$\frac{1}{R} = \beta \tag{C.9}$$

C3. Log-linearization

Using the convention that $\widehat{x} = (x - \overline{x})/\overline{x}$ denote deviations from steady state values, the log-linearized first order condition for labor supply can be written as

$$\hat{c}_t - \left(\alpha + \frac{N}{1-N}\right)\hat{n}_t = \gamma_t + \alpha\left(\hat{k}_t\right) \tag{C.10}$$

The resource constraint is:

$$\frac{\bar{C}}{\bar{K}}\hat{c}_t + \hat{k}_{t+1} = (1-\delta)\,\hat{k}_t - \alpha\frac{\bar{Y}}{\bar{K}}\hat{k}_t + (1-\alpha)\,\frac{\bar{Y}}{\bar{K}}\bar{N}\hat{n}_t + \frac{\bar{Y}}{\bar{K}}\hat{\gamma}_t \tag{C.11}$$

and the Euler equation becomes

$$0 = E_t\beta\left[\hat{c}_t + \hat{c}_{t+1} + \beta\bar{r}\left[\hat{\gamma}_{t+1} - (1-\alpha)\left(\hat{k}_{t+1} - \hat{n}_{t+1}\right)\right]\right] \tag{C.12}$$

C4. Model Calibration and Generation of the Synthetic Dataset

We calibrate the model to a quarterly setting using values typically used for simulating the US time series in the literature and discussed in Prescott (1986a) or Rebelo and King (1999). The values chosen for the parameters are presented in Table C.1.

Appendix D. Empirical Application

Using the *EU KLEMS* dataset,I can consider the following industries as in Table D.2

Appendix E. Variables

I get my data from the *EU KLEMS* dataset and from Statistic Denmark[1]: the period of the sample is 1970-2000. For my Growth Accounting exercise I consider the following time series

- Gross value added at constant basic prices (in millions of Danish Krones)
- Number of persons engaged (thousands)
- labor compensation (in millions of Danish Krones)
- Capital compensation (in millions of Danish Krones)
- Growth rate of gross output volume (% per year)
- Contribution of intermediate inputs to output growth (percentage points)
- Contribution of intermediate energy inputs to output growth (percentage points)
- Contribution of intermediate material inputs to output growth (percentage points)
- Contribution of intermediate services inputs to output growth (percentage points)
- Danish Investment divided into
  1. Residential structures
  2. Non-residential structures
  3. Infrastructure
  4. Transport equipment
  5. Computing equipment
  6. Communications equipment
  7. Other machinery and equipment
  8. Products of agriculture and forestry
  9. Other products
  10. Software
  11. Other intangibles

[1] `http://www.dst.dk/HomeUK.aspx`

Table C.1.: Stochastic growth model: parameters and calibration values

Parameter	**Definition**	**Value**	**Source**
β	utility discount factor (yearly)	0.99	Data
$\bar{R}$	average real interest factor (yearly)	1.0101	Data
$\bar{\gamma}$	technology	1	Theory
δ	depreciation rate of physical capital	0.04	Data
α	capital elasticity in production	0.33	Data
ρ	autocorrelation of TFP term A_t	0.95	Theory

Table D.2.: *EU KLEMS* Industries

DESCRIPTION	***CODE***
AGRICULTURE, HUNTING, FORESTRY AND FISHING	AtB
MINING AND QUARRYING	C
FOOD , BEVERAGES AND TOBACCO	15t16
TEXTILES, TEXTILE , LEATHER AND FOOTWEAR	17t19
WOOD AND OF WOOD AND CORK	20
PULP, PAPER, PAPER , PRINTING AND PUBLISHING	21t22
Coke, refined petroleum and nuclear fuel	23
Chemicals and chemical	24
Rubber and plastics	25
OTHER NON-METALLIC MINERAL	26
MACHINERY, NEC	29
ELECTRICAL AND OPTICAL EQUIPMENT	30t33
TRANSPORT EQUIPMENT	34t35
MANUFACTURING NEC; RECYCLING	36t37
ELECTRICITY, GAS AND WATER SUPPLY	E
CONSTRUCTION	F
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	50
Wholesale trade and commission trade, except of motor vehicles and motorcycles	51
Retail trade, except of motor vehicles and motorcycles; repair of household goods	52
HOTELS AND RESTAURANTS	H
POST AND TELECOMMUNICATIONS	64

C. Appendix to Chapter 4

Appendix F: A Model of ICT Spillovers and Technological Space

The investment and the possible spillover effects can be modeled modifying the framework introduced by Bloom et al. (2007). Similar to Jones and Williams (1998) who study business stealing and knowledge spillovers, in the basic assumptions a set of firms can invest in only one technological good, ICT, which may produce positive externalities, and face two different spaces: a *geographical* space S_{MKT} which also corresponds to the market space, where firms compete in their own neighborhood, and a *technological* space, S_{TECH}, where units of production can receive positive externalities. The setup of the model is based on a two-stage game, where there are two different types of firms which can interact: the technological ones (belonging to the group $TECH$) and traditional ones (which are grouped in $NON\ TECH$). During the first period only technological firms can decide the amount of their own investment in ICT, which is going to be given in the second stage, when knowledge may spill out enhancing TFP to $TECH$ firms in a space S_{TECH}. Moreover, at the same time, firms in each industry j in the same S_{MKT} can enter into competition. The firms in the technological space do not overlap with the ones in the geographical. In other words, a generic technological firm 0 interacts with firms in S_{TECH} only in the innovations in the first stage, while it competes with the firms j in the product firms. area.[1]

F1. Stage 2

Firm 0 faces a profit function which is common to all the other units of production in industry j of the same type:

$$\Pi_0 = \begin{cases} \pi_0\left(va_0, VA_j, ICT\ TFP_0\right) & if\ 0 \in TECH \\ \pi_0\left(va_0, VA_j\right) & otherwise \end{cases} \tag{F.1}$$

which is function of its own value added va_0, the aggregate value of industry i ($VA_i = \sum va_i$) and, if the firm belongs to the technological group, also by the total factor productivity generated by the investment in ICT $ICT\ TFP$. Solving for the second stage Nash decision, it yields

$$y_0^* = f\left(y_0, ICT_0, \overline{ICT}_{SPACE-0}\right) \tag{F.2}$$

which is concave, increasing in ICT_0, and decreasing in the average investment in ICT of the competitors of the firm 0 ($\overline{ICT}_{SPACE-0}$).

[1] For the implication of this last assumptions on the empirical part, see Section 5.

F2. Stage 1

Firm 0 benefits from the innovations produced by its own ICT investment, ICT_0 and with the possible spillovers from firms close to the technological space, which could be defined as a positive fraction ρ of the TFP gorwth:

$$ICT\ TFP_0 = \phi\left(ICT_0, \rho_0 \overline{ICT}_{SPACE-0}\right) \tag{F.3}$$

where ϕ (common to all the firms of the space) is non-decreasing and concave in both arguments, i.e.there are only positive spillovers. Thus firm 0 solves the following maximization problem:

$$\max_{ICT_0} V^0 = \Pi\left(\phi\left(ICT_0, \rho_0 \overline{ICT}_{SPACE-0}\right), \overline{ICT}_{SPACE-0}\right) - ICT_0 \tag{F.4}$$

assuming that firm belongs to the same technological space, $\overline{ICT}_{SPACE_0}$ not involving $ICT\ TFP_0$.[2] The first order condition is

$$\Pi_1 \phi_1 - 1 = 0 \tag{F.5}$$

By comparative statistics, spillovers can be measured in two different ways: the *real* spillovers can be expressed as

$$\frac{\partial^2 V_0}{\partial ICT_j ICT_0} = \Pi_1 \phi_{1j} + \Pi_{11} \phi_1 \phi_j \tag{F.6}$$

or as *knowledge* spillovers

$$\frac{\partial ICTTFP_0}{\partial ICT_j} = \Pi_1 \phi_{1j} + \Pi_{11} \phi_1 \phi_j \rho \tag{F.7}$$

The importance of the spillover is given by the values of ϕ_{1j} and ρ. If $\phi_{1j} > 0$, firm 0's ICT investment is positively related to the ICT invested by firms in the same technology space until the diminishing returns in knowledge production are not high. While if $\phi_{1j} = 0$ with diminishing returns (i.e. $\Pi_1 \phi_{1j} + \Pi_{11} \phi_1 \phi_j < 0$), then ICT is negatively related to investment in new technology, which means that only firms very near in the productivity frontier can spill the others.

[2] Another assumption of the model is that firms belonging to the technological space do not overlap with the product space.

Appendix G. Estimating TFP Index

In order to estimate a measure of TFP Index we consider the difference between the actual output and the one estimated from a restricted version of translog production function, i.e. a Cobb Douglas with Hicks neutral technology for firm i, industry j and time t:

$$\ln y_{it}^{j} = \beta_0 + \beta_n \ln n_{it}^{j} + \beta_k \ln k_{it}^{j} + TFP_{it}^{j} + \epsilon_{it}^{j} \tag{G.8}$$

where y is the firm's output measured as value added, n is the free variable inputs labor and k is the state variable capital. The error has two non observable component, TFP_{it}^{j}, which has an impact on the firm's decision choice and the error term ϵ_{it}^{j} which is uncorrelated with input choices. TFP_{it}^{j} is not observed by the researcher and can create the simultaneity problem in production function, which have been put in evidence by Marschak and Andrews (1944), giving inconsistent OLS results. In order to avoid this problem and assuming that employment can be freely adjusted, we use the methodology introduced by Olley and Pakes (1996) and extend by Levinsohn and Petrin (2003), which considers the intermediated goods used by the firm as instruments for controlling the correlations between capital and shocks. Moreover, as in Barba Navaretti et al. (2008), we estimate a production function for each ATECO 2 digit, which are defined in Appendix B, for avoiding the strict assumption of common technology among sectors.

Appendix H. ATECO Classification

Table H.1.: Industries and ATECO classification.

Description	**ATECO**	ICT
Mining of coal and lignite; extraction of peat	10	-
Extraction of crude petroleum and natural gas and services	11	-
Mining of uranium and thorium ores	12	-
Mining of metal ores	13	-
Other mining and quarrying	14	-
Food and beverages	15	-
Tobacco	16	-
Textiles	17	-
Wearing Apparel, Dressing And Dying Of Fur	18	-
Leather, leather and footwear	19	-
wood and of wood and cork	20	-
Pulp, paper and paper	21	-
Printing, publishing and reproduction	22	User
Coke, refined petroleum and nuclear fuel	23	-
Chemicals and chemical	24	-
Rubber and plastics	25	-
Other non-metallic mineral	26	-
Basic metals	27	-
Fabricated metal	28	-
Machinery, nec	29	User
Office, accounting and computing machinery	30	Producer
Electrical machinery and apparatus, nec	31	Producer
Radio, television and communication equipment	32	Producer
Medical, precision and optical instruments	33	Producer
Motor vehicles, trailers and semi-trailers	34	-
Other transport equipment	35	User
Manufacturing nec	36	-
Recycling	37	-

Table H.2.: Industries in the datasets.

		1998-2000				2001-2003			
ATECO		N.obs	ICT	IT	C	N. obs	ICT	IT	C
10	-	1	100	100	100	1	100	100	100
11	-	0	-	0	-	0	-	-	-
12	-	0	-	0	-	0	-	-	-
13	-	0	-	0	-	0	-	-	-
14	-	1	100	100	100	0	-	-	-
15	-	429	75	73	71	329	73	73	34
16	-	2	100	100	100	0	-	-	-
17	-	369	79	76	75	231	81	69	35
18	-	161	85	83	81	92	89	76	39
19	-	206	75	73	73	107	82	68	35
20	-	131	76	73	73	74	74	66	38
21	-	114	82	82	79	85	78	65	27
22	U	147	86	84	80	71	76	56	17
23	-	12	75	75	75	19	68	53	32
24	-	194	82	78	77	172	81	70	36
25	-	226	79	77	76	169	73	67	33
26	-	245	79	77	76	179	72	60	30
27	-	143	80	78	77	114	79	68	33
28	-	603	78	78	75	386	79	68	32
29	U	597	86	82	80	409	88	78	38
30	P	26	73	62	73	7	100	86	71
31	P	160	84	80	80	106	86	79	42
32	P	124	83	80	79	62	85	79	44
33	P	110	87	85	85	58	86	78	33
34	-	79	79	73	77	45	82	80	54
35	U	42	86	86	83	24	83	71	46
36	-	288	81	80	78	183	81	70	32
37	-	1	100	100	100	1	100	100	100

P: ICT Producer, *U*: ICT User,

Bibliography

T. A. Abbott, Z. Griliches, and J. Hausmann. Short run movements in productivity: Market power versus capacity utilization. mimeo, Harvard University, 1989.

D. Acemoglu. Why do new technologies complement skills? directed technical change and wage inequality. *The Quarterly Journal of Economics*, 113(4):1055–1089, November 1998.

D. Acemoglu. Directed technical change. *Review of Economic Studies*, 69(4):781–809, October 2002.

D. Acemoglu, P. Aghion, and F. Zilibotti. Distance to frontier, selection, and economic growth. *Journal of the European Economic Association*, 4(1):37–74, March 2006.

P. Aghion and R. Griffith. Competition and growth reconciling theory and evidence. *MIT Press*, 2005.

P. Aghion and P. Howitt. A model of growth through creative destruction. *Econometrica*, 60(2):323–51, March 1992.

S. Aiyar and C.-J. Dalgaard. Total factor productivity revisited: A dual approach to development accounting. IMF Staff Papers 52/1, International Monetary Fund, Jan. 2005.

G. A. Akerlof, A. K. Rose, J. L. Yellen, and H. Hessenius. East germany in from the cold: The economic aftermath of currency union. *Brookings Papers on Economic Activity*, 22(1991-1):1–106, 1991.

J. Albrecht, A. Bjorklund, and S. Vroman. Is there a glass ceiling in sweden? *Journal of Labor Economics*, 21:145–177, 2003.

J. Albrecht, A. Bjorklund, and S. Vroman. Counterfactual distribution with sample selection adjustments: Econometric theory and an application to the netherlands. mimeo, Georgetown University, 2006.

C. T. Altan. La nostra italia. *Feltrinelli, Milano*, 1986.

S. Ambler and A. Paquet. Stochastic depreciation and the business cycle puzzle. *International Economic Review*, 35:101–116, 1994.

C. Antonelli and F. Quatraro. The effects of biased technological change on total factor productivity.empirical evidence from a sample of oecd countries. Technical report, Collegio Carlo Alberto, June 2008.

M. Arellano and S. Bond. Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *Review of Economic Studies*, 58(2):277–97, April 1991.

K. Arrow. The economic implications of learning by doing. *Review of Economic Studies*, 94(29):155–73, June 1962.

K. Arrow, B. C. Hollis, B. S. Minhas, and R. M. Solow. Capital-labor substitution and economic efficiency. *Review of Economics and Statistics*, 43(2):225–50, August 1961.

D. H. Autor, L. F. Katz, and M. S. Kearney. Trends in u.s. wage inequality: Reassessing the revisionists. NBER Working Papers 11627, National Bureau of Economic Research, Inc, Sept. 2005.

M. N. Baily and R. J. Gordon. Measurement issues in the productivity slowdown and the explosion of computer power. *Brookings Papers on Economic Activity*, 2:347–420, 1988.

B. H. Baltagi and J. M. Griffin. A general index of technical change. *Journal of Political Economy*, 96(1):20–41, February 1988.

G. Barba Navaretti, M. Bugamelli, R. Faini, F. Schivardi, and A. Tucci. Come sta cambiando la specializzazione produttiva dell'italia. *in Baldwin, Barba Navaretti, Boeri, Come sta cambiando l'Italia, il Mulino, Bologna*, 2008.

R. J. Barro. Notes on growth accounting. *Journal of Economic Growth*, 4:119–137, 1999.

R. J. Barro and X. Sala-I-Martin. *Economic Growth*. MIT Press, Cambridge, 2 edition, 2005.

E. Bartelsman. Of empty boxes: Returns to scale revisited. *Economics Letters*, 49(1): 59–67, July 1995.

E. Bartelsman and M. Doms. Understanding productivity: Lessons from longitudinal microdata. *Journal of Economic Literature*, 38(3):569–594, September 2000.

E. Bartelsman and J. Hinloopen. De verzilvering van een groeibelofte. *in ICT en de Economie, Koninklijke Vereniging voor Staathuishoudkunde, Preadviezen*, 2000.

E. Bartelsman and J. Hinloopen. Unleashing animal spirits: Investment in ict and economic growth. *in In Soete, L. and ter Weel, B., The Economics of the Digital Economy. Edward Elgar.*, 2004.

O. Basdevant. On applications of state-space modelling in macroeconomics. Reserve Bank of New Zealand Discussion Paper Series DP2003/02, Reserve Bank of New Zealand, Apr. 2003.

S. Basu. Procyclical productivity: Increasing returns or cyclical utilization? *The Quarterly Journal of Economics*, 111(3):719–51, August 1996.

S. Basu and J. G. Fernald. Returns to scale in u.s. production: Estimates and implications. *Journal of Political Economy*, 105(2):249–83, April 1997.

S. Basu and D. N. Weil. Appropriate technology and growth. *The Quarterly Journal of Economics*, 113(4):1025–1054, November 1998.

S. Basu, J. G. Fernald, and N. Oulton. The case of the missing productivity growth, or does information technology explain why productivity accelerated in the united states but not in the united kingdom? In *NBER Macroeconomics Annual 2003, Volume 18*, NBER Chapters, pages 9–82. National Bureau of Economic Research, Inc, April 2004.

W. J. Baumol. Productivity growth, convergence, and welfare. what the long run data show. *American Economic Review*, 76(5):1072–85, 1996.

G. Beccattini. Distretti industriali e made in italy. le basi socioculturali del nostro sviluppo. *Bollati Borignhieri, Torino*, 1998.

A. B. Bernard and C. I. Jones. Comparing apples to oranges: Productivity convergence and measurement across industries and countries. *American Economic Review*, 86(5): 1216–38, December 1996.

J. I. Bernstein and M. I. Nadiri. Interindustry r&d spillovers, rates of return, and production in high-tech industries. *American Economic Review*, 78(2):429–34, May 1988.

H. P. Binswanger. The measurement of technical change biases with many factors of production. *American Economic Review*, 64(6):964–76, December 1974.

S. E. Black and L. M. Lynch. What's driving the new economy?: the benefits of workplace innovation. *Economic Journal*, 114(493):F97–F116, 02 2004.

O. Blanchard. The medium run. *Brookings Papers on Economic Activity*, 28(1997-2): 89–158, 1997.

O. Blanchard and M. Kremer. Disorganization. *The Quarterly Journal of Economics*, 112(4):1091–1126, November 1997.

N. Bloom, M. Schankerman, and J. Van Reenen. Identifying technology spillovers and product market rivalry. NBER Working Papers 13060, National Bureau of Economic Research, Inc, Apr. 2007.

J. Bound and G. Johnson. Changes in the structure of wages in the 1980's: An evaluation of alternative explanations. *American Economic Review*, 82(3):371–92, June 1992.

T. F. Bresnahan, E. Brynjolfsson, and L. M. Hitt. Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal of Economics*, 117(1):339–376, February 2002.

W. A. Brock and S. N. Durlauf. Discrete choice with social interactions. *Review of Economic Studies*, 68(2):235–60, April 2001.

M. Bruno and J. Sachs. *The Economics of Worldwide Stagflation.* Basil Blackwell, Oxford, 1985.

E. Brynjolfsson and L. M. Hitt. Computing productivity: Firm-level evidence. *The Review of Economics and Statistics*, 85(4):793–808, November 2003.

M. C. Burda and J. Hunt. From reunification to economic integration: Productivity and labor market in eastern germany. *Brookings Papers on Economic Activity*, 2: 1–71, 2001.

M. C. Burda, B. Fitzenberger, A. Lembcke, and T. Vogel. Unionization, stochastic dominance, and compression of the wage distribution: Evidence from germany. SFB 649 Discussion Papers SFB649DP2008-041, Sonderforschungsbereich 649, Humboldt University, Berlin, Germany, Aug. 2008.

C. Burnside, M. Eichenbaum, and S. Rebelo. Capital utilization and returns to scale. *In NBER Macroeconomics Annual 1995, ed. Ben S. Bernanke and Julio J. Rotemberg*, pages 67–110, 1995.

R. J. Caballero. *Specificity and the Macroeconomics of Restructuring.* MIT Press, Cambridge, 2007.

R. J. Caballero and R. K. Lyons. External effects in u.s. procyclical productivity. *Journal of Monetary Economics*, 29(2):209–225, April 1992.

C. A. Cameron and P. K. Trivedi. Microeconometrics using stata. *Stata Press, College Station*, 2008.

F. Canova. *Methods for Applied Macroeconomic Research.* Princeton University Press, Princeton, 2007.

F. Canova and M. Ciccarelli. Forecasting and turning point predictions in a bayesian panel var model. *Journal of Econometrics*, 120(2):327–359, June 2004.

F. Caselli. Accounting for cross-country income differences. In P. Aghion and S. Durlauf, editors, *Handbook of Economic Growth*, volume 1 of *Handbook of Economic Growth*, chapter 9, pages 679–741. Elsevier, September 2005.

D. W. Caves, L. R. Christensen, and W. E. Diewert. The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica*, 50 (6):1393–1414, November 1982.

R. Chambers. *Applied Production Analysis. A Dual Approach.* Cambridge University Press, Cambridge, 1988.

B. Chen and P. A. Zadrozny. Estimated u.s. manufacturing production capital and technology based on an estimated dynamic structural economic model. *Journal of Economic Dynamics and Control*, 33(7):1398–1418, July 2009.

S. Choi and J.-V. Ròs-Rull. Understanding the dynamics of labor share: The role of noncompetitive factor prices. University of minnesota,mimeo, Economics, 2008.

L. Christensen, D. W. Jorgenson, and L. Lau. Trascendental logarithmic production frontiers. *Review of Economics and Statistics, 55, 26-45*, 1973.

L. Christiano. A survey of measures of capacity utilization. IMF Staff Papers 28, International Monetary Fund, 1981.

L. Christiano, M. Eichenbaum, and C. Evans. Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy*, pages 1–45, February 2005.

T. Cogley and T. J. Sargent. Drift and volatilities: Monetary policies and outcomes in the post wwii u.s. *Review of Economic Dynamics*, 8(2):262–302, April 2005.

T. F. Cooley and E. C. Prescott. Economic growth and business cycles, in frontiers of business cycle research (ed. thomas f. cooley). *Princeton University Press*, Princeton University Press, 1995.

C. A. Corrado and J. Mattey. Capacity utilization. *Journal of Economic Perspectives*, 11(1):151–67, Winter 1997.

C. A. Corrado, C. R. Hulten, and D. E. Sichel. Intangible capital and economic growth. NBER Working Papers 11948, National Bureau of Economic Research, Inc, Jan. 2006.

N. Crafts. The solow productivity paradox in historical perspective. CEPR Discussion Papers 3142, C.E.P.R. Discussion Papers, Jan. 2002.

C. M. Dahl, H. C. Kongsted, and A. S. rensen rensen rensen rensen. Ict and productivity growth in the 1990's panel data evidence on europe. Cbs working paper, Copenhagen Business School, June 2009.

F. Daveri and C. Jona-Lasinio. Italy's decline: Getting the facts right. *Giornale degli Economisti*, 64(4):365–410, December 2005.

F. Daveri and C. Jona-Lasinio. Off-shoring and productivity growth in the italian manufacturing industries. *CESifo Economic Studies*, 54(3):414–450, September 2008.

B. De Borger and K. Kerstens. The malmquist productivity index and plant capacity utilization. *Scandinavian Journal of Economics*, 102(2):303–10, June 2000.

G. Debreu. The coefficient of resource utilization. *Econometrica*, 19(3):273–92, July 1951.

D. Dejong and C. Dave. *Structural Macroeconometrics.* Princeton University Press, Princeton, 2007.

D. DeJong, B. F. Ingram, and C. H. Whiteman. A bayesian approach to dynamic macroeconomics. *Journal of Econometrics*, 98(2):203–223, October 2000.

E. Denison. Source of economic growth in the united states and the alternative before us. *Committee for Economic Development*, 1962.

E. Denison. The unimportance of the embodiment question. *American Economic Review*, 54:90–4, March 1964.

E. Denison. Some major issues in productitivy analysis: An examination of the estimates by jorgenson and griliches. *Survey of Current Business*, 5(2):1–27, 1972.

M. Denny, M. Fuss, and L. Waverman. The measurement and the interpretation of total factor productivity in regulated industries with an application to canadian telecommunication. In T. G. Cowing and R. Stevenson, editors, *Productivity Measurement in Regulated Industries*. Academic Press, 1981.

P. Diamond. Aggregate demand management in search equilibrium. *Journal of Political Economy*, 90(5):881–894, October 1982.

D. A. Dickey and W. A. Fuller. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74:427–431, 1979.

W. E. Diewert. Exact and superlative index numbers. *Journal of Econometrics*, 4: 115–45, 1976.

W. E. Diewert. The theory of total factor productivity measurement in regulated industries. In T. G. Cowing and R. Stevenson, editors, *Productivity Measurement in Regulated Industries*. Academic Press, 1981.

W. E. Diewert and K. J. Fox. On the estimation of returns to scale, technical progress and monopolistic markups. *Journal of Econometrics*, 145(1-2):174–193, July 2008.

W. E. Diewert and A. O. Nakamura. The measurement of productivity for nations. In J. Heckman and E. Leamer, editors, *Handbook of Econometrics*, volume 6 of *Handbook of Econometrics*, chapter 66. Elsevier, January 2007.

J. DiNardo, N. M. Fortin, and T. Lemieux. Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. *Econometrica*, 64(5):1001–44, September 1996.

R. Esposti. Stochastic technical change and procyclical tfp the italian agriculture case. *Journal of Productivity Analysis*, 14:119–41, 2000.

S. Fabiani, F. Schivardi, and S. Trento. Ict adoption in italian manufacturing: firm-level evidence. *Industrial and Corporate Change*, 14(2):225–249, April 2005.

R. Färe, S. Grosskopf, B. Lindgren, and P. Ross. Productivity developments in swedish hospitals: A malmquist output index approach. *Southern Illinois University at Carbondale. Department of Economics. Working Paper*, 1989.

R. Färe, S. Grosskopf, B. Lindgren, and P. Ross. Productivity changes in swedish pharmacies 1980-1989: A nonparametric malmquist approach. *Journal of Productivity Analysis*, 3(1:2):85–101, June 1992.

R. Färe, S. Grosskopf, M. Norris, and Z. Zhang. Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review*, 84(1): 66–83, March 1994.

R. Färe, E. Grifell-Tatje, S. Grosskopf, and C. Lovell. Biased technical change and the malmquist productivity index. *Scandinavian Journal of Economics*, 99(1):119–27, March 1997.

M. J. Farrell. The measurement of productivity efficiency. *Journal of the Royal Statistical Society. Series A. General.*, 120(3):253–82, 1957.

S. Firpo, N. M. Fortin, and T. Lemieux. Unconditional quantile regression. *Econometrica*, 77(3):953–973, 5 2009.

H. O. Fried, L. Knox, and S. Schmidt. Efficiency and productivity. In K. L. Harold O. Fried and S. Schmidt, editors, *The Measurement of Productive Efficiency and Productivity Growth*, volume 3, pages 3–91. Oxford University Press, 2008.

E. L. Glaeser and J. Scheinkman. Non-market interactions. NBER Working Papers 8053, National Bureau of Economic Research, Inc, Dec. 2000.

E. L. Glaeser, H. D. Kallal, J. A. Scheinkman, and A. Shleifer. Growth in cities. *Journal of Political Economy*, 100(6):1126–52, December 1992.

R. Goldsmith. *The National Wealth of the United States in the Post-war Period*. Princeton University Press, Princeton, 1995.

F. M. Gollop and M. J. Roberts. Environmental regulations and productivity growth: The case of fossil-fueled electric power generation. *Journal of Political Economy*, 91 (4):654–74, August 1983.

P. Gomme and J. Greenwood. On the cyclical allocation of risk. *Journal of Economic Dynamics and Control*, 19(1-2):91–124, 1995.

R. J. Gordon. *The Measurement of Durable Goods Prices*. University of Chicago Press, Chicago, 1990.

R. J. Gordon. Are procyclical productivity fluctuations a figment of measurement error? mimeo 0434, Northwestern University, 1992.

R. J. Gordon. Does the "new economy" measure up to the great inventions of the past? *Journal of Economic Perspectives*, 14(4):49–74, Fall 2000.

R. J. Gordon. Exploding productivity growth: Context, causes, and implications. *Brookings Papers on Economic Activity*, 2003(2):207–279, 2003.

W. Greene. Econometric analysis. *Prentice Hall, New York*, 2008a.

W. Greene. The economeric approach to efficiency analysis. In H. Fried, K. Lovell, and S. Schmidt, editors, *The Measurement of Productive Efficiency and Productivity Growth*, chapter 3, pages 251–420. Oxford University Press, 2008b.

J. Greenwood, Z. Hercowitz, and G. W. Huffman. Investment, capacity utilization, and the real business cycle. *American Economic Review*, 78(3):402–17, 1988.

J. Greenwood, Z. Hercowitz, and P. Krusell. Long-run implications of investment-specific technological change. *American Economic Review*, 87(3):342–62, June 1997.

R. Griffith and H. Harmgart. Retail productivity. IFS Working Papers W05/07, Institute for Fiscal Studies, Mar. 2005.

Z. Griliches. Issues in assessing the contribution of research and development to productivity growth. *Bell Journal of Economics*, 10(1):92–116, Spring 1979.

Z. Griliches. R&d and the productivity slowdown. NBER Working Papers 0434, National Bureau of Economic Research, Inc, Sept. 1980.

Z. Griliches. The search for r&d spillovers. *Scandinavian Journal of Economics*, 94(0): S29–47, Supplement 1992.

Z. Griliches. Productivity, r&d, and the data constraint. *American Economic Review*, 84(1):1–23, March 1994.

Z. Griliches. The discovery of the residual: A historical note. *Journal of Economic Literature*, 34(3):1324–1330, September 1996.

L. Guiso and F. Schivardi. Spillovers in industrial districts. *Economic Journal*, 117 (516):68–93, 01 2007.

L. Guiso, P. Sapienza, and L. Zingales. Long term persistence. NBER Working Papers 14278, National Bureau of Economic Research, Inc, Aug. 2008.

R. Hall and C. I. Jones. Why do some countries produce so much more output per worker than others? *The Quarterly Journal of Economics*, 114(1):83–116, February 1999.

R. E. Hall. The relation between price and marginal cost in u.s. industry. *Journal of Political Economy*, 96(5):921–47, October 1988.

R. E. Hall. Invariance properties of solow's productivity residual. In P. Diamond, editor, *Growth, Productivity, Unemployment*, pages 71–112. MIT PRESS, 1990.

S. G. Hall and O. Basdevant. Measuring the capital stock in russia: An unobserved component model. *Economic Change and Restructuring*, 35(4):365–70, 2002.

J. Hamilton. *Time Series Analysis*. Princeton University Press, Princeton, 1994.

G. D. Hansen. Indivisible labor and the business cycle. *Journal of Monetary Economics*, 16(3):309–327, November 1985.

G. D. Hansen and E. C. Prescott. Capacity constraints, asymmetries, and the business cycle. *Review of Economic Dynamics*, 8(4):850–865, October 2005.

S. G. Harrison and M. Weder. Did sunspot forces cause the great depression? *Journal of Monetary Economics*, 53(7):1327–1339, October 2006.

A. Harvey. *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge University Press, Cambridge, 1989a.

A. Harvey and S. Wren-Lewis. Stochastic trends in dynamic regression models: An application to the employment-output equations. *Economic Journal*, 96(384):975–85, December 1986.

A. C. Harvey. *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge University Press, Cambrdige, 1989b.

W. Hendricks and R. W. Koenker. Hierarchical spline models for conditional quantiles and the demand for electricity. *Journal of the American Statistical Association*, 87: 58–68, 1982.

C.-T. Hsieh. What explains the industrial revolution in east asia? evidence from factor markets. *American Economic Review*, 92(2):502–26, 2002.

T. N. Hubbard. The demand for monitoring technologies: The case of trucking. *The Quarterly Journal of Economics*, 115(2):533–560, May 2000.

C. R. Hulten. Productivity change, capacity utilization, and the sources of efficiency growth. *Journal of Econometrics*, 33(1-2):31–50, 1986.

C. R. Hulten. The measurement of capital. *Fifty Years of Economic Measurement, E.R. Berndt and J.E. Triplett (eds.), Studies in Income and Wealth, The National Bureau of Economic Research, Chicago: The University of Chicago Press*, 54(June):119–152, 1990.

C. R. Hulten. Growth accounting when technical change is embodied in capital. *American Economic Review*, 82(4):964–980, September 1992.

C. R. Hulten. Growth accounting. NBER Working Papers, Paper prepared for the Handbook of the Economics of Innovation, Bronwyn H. Hall and Nathan Rosenberg (eds.), Elsevier-North Holland, in process 15341, National Bureau of Economic Research, Inc, Sept. 2009.

K. S. Im, M. H. Pesaran, and Y. Shin. Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115(1):53–74, July 2003.

P. N. Ireland. Technology shocks and the business cycle: An empirical investigation. *Journal of Economic Dynamics and Control*, 25(5):703–719, May 2001.

V. Jacob, S. C. Sharma, and R. Grabowski. Capital stock estimates for major sectors and disaggregated manufacturing in selected oecd countries. *Applied Economics*, 29 (5):563–79, 1997.

A. B. Jaffe, R. G. Newell, and R. N. Stavins. Technological change and the environment. In K. G. Mäler and J. R. Vincent, editors, *Handbook of Environmental Economics*, volume 1 of *Handbook of Environmental Economics*, chapter 11, pages 461–516. Elsevier, June 2003.

J. Jalava and M. Pohjola. The roles of electricity and ict in economic growth: Case finland. *Explorations in Economic History*, 45(3):270–287, July 2008.

R. Jensen. The digital provide: Information (technology), market performance, and welfare in the south indian fisheries sector. *The Quarterly Journal of Economics*, 122 (3):879–924, 08 2007.

C. I. Jones and P. M. Romer. The new kaldor facts: Ideas, institutions, population, and human capital. NBER Working Papers 15094, National Bureau of Economic Research, Inc, June 2009.

C. I. Jones and J. C. Williams. Measuring the social return to r&d. *The Quarterly Journal of Economics*, 113(4):1119–1135, November 1998.

D. W. Jorgenson. The embodiment hypothesis. *Journal of Political Economy*, 74:1–17, February 1966.

D. W. Jorgenson. Econometric methods for modelling producer. In Z. Griliches and M. D. Intriligator, editors, *Handbook of Econometrics*, volume 3, pages 1841–1180. North-Holland, 1986.

D. W. Jorgenson. *Econometric Modeling of Producer Behavior.* MIT Press, Cambridge, 2001.

D. W. Jorgenson. Accounting for growth in the information age. In P. Aghion and S. Durlauf, editors, *Handbook of Economic Growth*, volume 1 of *Handbook of Economic Growth*, chapter 10, pages 743–815. Elsevier, September 2005.

D. W. Jorgenson and B. Fraumeni. Relative prices and technical change. In E. R. Berndt and B. C. Field, editors, *Modelling and Measuring Natural Resource Substitution.* MIT Press, 1981.

D. W. Jorgenson and Z. Griliches. The explanation of productivity change. *Review of Economic Studies*, 34:249–283, 1967.

D. W. Jorgenson and Z. Griliches. Issue in growth accounting: A reply to edward f. denison. *Survey of Current Business*, 52:65–94, 1972.

D. W. Jorgenson and H. Jin. Econometric modeling of technical change. *mimeo, Harvard University*, November 2008.

D. W. Jorgenson and K. Vu. Information technology and the world economy. *Scandinavian Journal of Economics*, 107(4):631–650, December 2005.

D. W. Jorgenson, F. Gollop, and B. M. Fraumeni. *Productivity and U.S. Economic Growth.* Harvard University Press, Cambridge, 1987.

D. W. Jorgenson, M. Ho, and K. Stiroh. Information technology and the american growth resurgence. *Cambridge: the MIT Press*, 2005.

J. A. Kahn and R. W. Rich. Tracking the new economy: using growth theory to detect changes in trend productivity. *Proceedings-Federal Reserve Bank of San Francisco*, November 2003.

N. Kaldor. Capital accumulation and economic growth. In F. Lutz and D. Hague, editors, *The Theory of Capital*, pages 177–222. St. Martin's Press, 1961.

R. Kalman. A new approach to linear filtering and prediction problems. *Journal of Basic Engineering, Transactions ASME*, 82(D):32–45, 1960.

L. F. Katz and K. M. Murphy. Changes in relative wages, 1963-1987: Supply and demand factors. *The Quarterly Journal of Economics*, 107(1):35–78, February 1992.

M. Katz and C. Shapiro. Technology adoption in presence of network externalities. *Journal of Political Economy*, 94(4):822–841, August 1986.

J. W. Kendrick. *Productivity Trends in the United States.* Princeton University Press, Princeton, 1961.

J. W. Kendrick and R. Sato. Factor prices, productivity, and economic growth. *American Economic Review*, 53(3):974–1003, December 1963.

C. Kennedy. Induced bias in innovation and the theory of distribution. *Economic Journal*, 74:541–47, 1964.

C.-J. Kim. Dynamic linear models with markov-switching. *Journal of Econometrics*, 60 (1-2):1–22, 1994.

C.-J. Kim and C. Nelson. *State-Space Models with Regime Switching. Classical and Gibbs-Sampling Approaches with Applications.* MIT Press, Cambridge, 2001.

R. G. King, C. I. Plosser, and S. T. Rebelo. Production, growth and business cycles : I. the basic neoclassical model. *Journal of Monetary Economics*, 21(2-3):195–232, 1988.

R. S. King and S. Rebelo. Resuscitating real business cycles. *Handbook of Macroeconomics, edited by J. B. Taylor and M. Woodford, Volume 1B, 9271007. Amsterdam: Elsevier*, 1999.

R. W. Koenker and G. J. Bassett. Regression quantiles. *Econometrica*, 46(1):33–50, January 1978.

T. C. Koopmans. An analysis of production as an efficient combination of activities. In T. Koopmans, editor, *Activity Analysis of Production and Allocation*, 13. Cowles Commission for Research in Economics, New York, 1951.

R. J. Kopp and V. K. Smith. Neoclassical modeling of nonneutral technological change: An experimental appraisal. *Scandinavian Journal of Economics*, 85(2):127–46, 1983.

P. Krugman. *The Age of Diminished Expectations.* MIT Press, Cambrdige, 1990.

P. Krusell, L. E. Ohanian, J.-V. Rìos-Rull, and G. L. Violante. Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica*, 68(5):1029–1054, September 2000.

S. Kumar and R. R. Russell. Technological change, technological catch-up, and capital deepening: Relative contributions to growth and convergence. *American Economic Review*, 92(3):527–548, June 2002.

F. E. Kydland and E. C. Prescott. The workweek of capital and its cyclical implications. *Journal of Monetary Economics*, 21(2-3):343–360, 1988.

F. E. Kydland and E. C. Prescott. Cyclical movements of the labor input and its implicit real wage. *Economic Review*, Q II:12–23, 1993.

T. Lancaster. Orthogonal parameters and panel data. *Review of Economic Studies*, 69 (3):647–66, July 2002.

Y. H. L. Lee and P. Schmidt. A production frontier model with flexible temporal variation in technical inefficiency. In H. Fried, K. Lovell, and S. Schmidt, editors, *The Measurement of Productive Efficiency and Productivity Growth*, chapter 8, pages 237–255. Oxford University Press, 1993.

J. Levinsohn and A. Petrin. Estimating production functions using inputs to control for unobservables. *Review of Economic Studies*, 70(2):317–341, 04 2003.

K. Lovell. The decomposition of malmquist productivity indexes. *Journal of Productivity Analysis*, 20(5):437–58, December 2003.

R. J. Lucas. On the mechanics of economic development. *Journal of Monetary Economics*, 22(1):3–42, July 1988.

J. A. F. Machado and J. Mata. Counterfactual decomposition of changes in wage distributions using quantile regression. *Journal of Applied Econometrics*, 20(4):445–465, 2005.

A. Maddison. Monitoring the world economy. Oecd, paris, Development Center Studies, 2005.

J. Mairesse and Z. Grilliches. Lheterogeneity in panel data: Are there stable production functions? In P. C. et al et al, editor, *Essays in Honour of Edmond Malinvaud*, Empirical Economics, pages 192–231. MIT Press, 1990.

S. Malmquist. Index numbers and indifference surfaces. *Trabajos de Estadistica*, 4: 209–242, 1953.

G. N. Mankiw, D. Romer, and D. N. Weil. A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, 107(2):407–37, May 1992.

C. F. Manski. Identification of endogenous social effects: The reflection problem. *Review of Economic Studies*, 60(3):531–42, July 1993.

J. Marschak and W. Andrews. Random simultaneous equations and the theory of production. *Econometrica*, 12:143–205, 1944.

A. Marshall. Principle of economics. *London, MacMillan*, 1890.

N. Matteucci, M. O'Mahony, C. Robinson, and T. Zwick. Productivity, workplace performance and ict: Industry and firm-level evidence for europe and the us. *Scottish Journal of Political Economy*, 52(3):359–386, 07 2005.

D. Mayes and G. Young. Improving estimates of the u.k. capital stock. *National Institute Economic Review*, pages 84–96, 1994.

B. Melly. Estimation of counterfactual distribution using quantile regression. *University of St Gallen, SIAW, mimeo*, 2006.

C. Milana and A. Zeli. The contribution of ict to production efficiency in italy: Firm-level evidence using data envelopment analysis and econometric estimations. OECD Science, Technology and Industry Working Papers 2002/13, OECD Directorate for Science, Technology and Industry, Sept. 2002.

J. Mokyr. *The Lever of Riches: Technological Creativity and Economic Progress*. Oxford University Press, Oxford, 1992.

J. Mokyr. Long-term economic growth and the history of technology. In P. Aghion and S. Durlauf, editors, *Handbook of Economic Growth*, volume 1 of *Handbook of Economic Growth*, chapter 17, pages 1113–1180. Elsevier, September 2005.

A. O. Nakamura and W. E. Diewert. The measurement of productivity for nations. *Handbook of Econometrics*, 6A, 2007.

W. D. Nordhaus. Productivity growth and the new economy. *Brookings Papers on Economic Activity*, 33(2002-2):211–265, 2002.

N. Nunn. Relationship-specificity, incomplete contracts, and the pattern of trade. *The Quarterly Journal of Economics*, 122(2):569–600, 05 2007.

R. Oaxaca. Male-female wage differentials in urban labor markets. *International Economic Review*, 14(3):693–709, October 1973.

OECD. Measuring capital, oecd manual. Technical report, OECD, Paris, 2001.

OECD. Measuring the information economy. Technical report, OECD, Paris, April 2002.

S. Olley and A. Pakes. The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6):1263–97, November 1996.

N. Oulton. Ict and productivity growth in the united kingdom. *Oxford Review of Economic Policy*, 18(3):363–379, 2002.

K. Pavitt. Sectoral patterns of technical change: Towards a taxonomy and a theory. *Research Policy*, 13:343–373, 1984.

P. C. Phillips and P. Perron. Testing for a unit root in time series regression. *Biometrika*, 75(2):335–346, 1988.

M. Porter. The competitive advantages of nations. *New York: Free Press*, 1990.

E. C. Prescott. Theory ahead of business cycle measurement. *Quarterly Review, Federal Reserve Bank of Minneapolis*, pages 9–22, 1986a.

E. C. Prescott. Theory ahead of business-cycle measurement. *Carnegie-Rochester Conference Series on Public Policy*, 25(1):11–44, January 1986b.

E. C. Prescott. Nobel lecture: The transformation of macroeconomic policy and research. *Journal of Political Economy*, 114(2):203–235, April 2006.

D. T. Quah. Twin peaks: Growth and convergence in models of distribution dynamics. *Economic Journal*, 106(437):1045–55, July 1996.

S. C. Ray and E. Desli. Productivity growth, technical progress, and efficiency change in industrialized countries: Comment. *American Economic Review*, 87(5):1033–39, December 1997.

M. Reinsdorf and M. Cover. Measurement of capital stocks, consumption of fixed capital, and capital services. *BEA, mimeo*, 2005.

J.-V. Ròos-Rull and R. Santaeulália-Llopis. Redistributive shocks and productivity shocks. University of minnesota, mimeo, Economics, 2009.

J. Robinson. The production function and the theory of capital. *The Review of Economic Studies*, 21(2):81–106, 1953.

W. Roeger. Can imperfect competition explain the difference between primal and dual productivity measures? estimates for u.s. manufacturing. *Journal of Political Economy*, 103(2):316–30, 1995.

P. M. Romer. Increasing returns and long-run growth. *Journal of Political Economy*, 94(5):1002–37, October 1986.

B. Rosenberg. Random coefficients models: the analysis of a cross section of time series by stochastically convergent parameter regression. *Annals of Social and Economic Measurement,2(4):399-428*, 1973.

P. A. Samuelson. A theory of induced innovation along kennedy, weiszacker lines. *Review of Economics and Statistics*, 47:343–56, 1965.

T. Sargent, N. Williams, and T. Zha. Shocks and government beliefs: The rise and fall of american inflation. *American Economic Review*, 96(4):1193–1224, September 2006.

P. Schotman and H. K. van Dijk. A bayesian analysis of the unit root in real exchange rates. *Journal of Econometrics*, 49(1-2):195–238, 1991.

J. Schumpeter. The theory of capitalism develpoment. *Harvard University Press, Cambridge*, 1934.

G. W. Schwert. Tests for unit roots: A monte carlo investigation. *Journal of Business & Economic Statistics*, 20(1):5–17, January 2002.

F. Sforzi. The quantitative importance of marshallian industrial districts in the italian economy. *in Pyke, Beccattini and Segenberger, Industrial Districts and Inter-Firm Cooperation in Italy, Geneva International Institute of Labour Studies*, 2000.

R. Shepard. *Costs and Production Functions.* Princeton University Press, Princeton, 1953.

R. Shepard. *Theory of Costs and Production Functions.* Princeton University Press, Princeton, 1970.

R. Sickles and M. Tsionas. A panel data model with nonparametric time effects. mimeo, Rice University, 2008.

C. A. Sims. Using a likelihood perspective to sharpen econometric discourse: Three examples. *Journal of Econometrics*, 95(2):443–462, April 2000.

M. Slade. Modeling stochastic and cyclical components of technological change. an application of kalman filter. *Journal of Econometrics*, 41:363–83, 1989.

B. Sliker. 2007 r&d satellite account methodologies: R&d capital stocks and net rates of return. R&d satellite account background paper, Bureau of Economic Analysis/National Science Foundation., December 2007.

R. M. Solow. Technical change and the aggregate production function. *Review of Economics and Statistics,39:312-320*, 1957.

K. J. Stiroh. Are ict spillovers driving the new economy? *Review of Income and Wealth*, 48(1):33–57, March 2002a.

K. J. Stiroh. Information technology and the u.s. productivity revival: What do the industry data say? *American Economic Review*, 92(5):1559–1576, December 2002b.

J. H. Stock and M. W. Watson. Business cycle fluctuations in us macroeconomic time series. *Handbook of Macroeconomics*, 1:3–64, June 1999.

T. ten Raa. *The Economics of Input-Output Analysis.* Cambridge University Press, Cambridge, 2005.

E. Thanassoulis, M. Portela, and O. Despic. Data envelopment analysis: The mathematical programming approach to efficiency analysis. In H. Fried, K. Lovell, and S. Schmidt, editors, *The Measurement of Productive Efficiency and Productivity Growth*, chapter 3, pages 251–420. Oxford University Press, 2008.

J. Tinbergen. Zur theorie der langfristigen wirtschaftstsentwicklung. *Weltwirtschaftliches Archiv*, 55(1):511–49, 1942.

L. Törnqvist. The bank of finland's consumption price index. *Bank of Finland Monthly Bulletin, 10, 1-8*, 1936.

J. E. Triplett. Concepts of quality in input and output price measures: A resolution of the user value resource cost debate. In M. F. Foss, editor, *The U.S. National Income and Product Accounts. Selected Topics. Studies in Income and Wealth*, volume 47, pages 296–311. University of Chicago Press, 1983.

B. van Ark. Measuring the new economy: An international comparative perspective. *Review of Income and Wealth*, 48(1):1–14, March 2002.

B. van Ark, M. O'Mahoney, and M. P. Timmer. The productivity gap between europe and the united states: Trends and causes. *Journal of Economic Perspectives*, 22(1): 25–44, Winter 2008.

J. Van Biesebroeck. Robustness of productivity estimates. *Journal of Industrial Economics*, 95, July 2006.

H. van der Wiel and G. van Leeuwen. Do ict spillovers matter? evidence from dutch firm-level data. CPB Discussion Papers 26, CPB Netherlands Bureau for Economic Policy Analysis, Nov. 2003.

M. Ward. The measurement of capital. the methodology of capital stock estimates in oecd countries. *OECD Paris*, 1976.

Y. Wen. Capacity utilization under increasing returns to scale. *Journal of Economic Theory*, 81(1):7–36, July 1998.

Selbständigkeitserklärung

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

Berlin, den 9.11.2009 Battista Severgnini,